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Obstacle or Opportunity: Exploring Energy Education Opportunities in a Low-Income Community

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Obstacle or Opportunity: Exploring Energy Education Opportunities in a Low-Income Community

by

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Thesis

Presented to the Faculty of the Graduate School of

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Dedication

For Tom Fry, the greatest teacher I ever had.

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Abstract

Obstacle or Opportunity: Exploring Opportunities for Energy Education in a Low-Income Community

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The University of Texas at Austin, 2012

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This thesis examines an effort to increase energy conservation in low-income housing communities through an educational program. The Saving Green Program offered at Foundation Communities in Austin, Texas attempts to educate residents about their energy usage and ways to reduce it. Activities include a class, an in-home energy visit, and energy feedback reports. We take several approaches in analyzing the program's impact. First, we conduct a descriptive characterization of participants with regards to income, household makeup, and electricity usage. We then interviewed program participants in order to assess impact and participant reaction. Finally, we conduct two quantitative analyses to measure effectiveness. These include a comparison between groups of participants and non-participants, and a comparison of participants' electricity usage after the program against their own usage before the program. Our descriptive assessment shows that most in our sample are either single seniors or households with multiple children. Their electricity usage varies however nearly half of load usually goes to cooling and their usage appears to be uncorrelated with income.

Load patterns are dictated more by apartment size than anything else. Interviews show that participants readily absorbed and disseminated information regarding plug loads, but had poor understanding of the importance of cooling load. Finally, our quantitative analysis shows, in accordance with the interviews, that participants did not exhibit any systematic change in electricity consumption in summer, however there is some evidence that winter load decreased after the program.

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Chapter 1: Introduction

1.1 MOTIVATION

Efforts to curb energy consumption take many different forms. One of the least discussed is energy education. Energy efficiency implementers often focus on technical solutions that require capital input; it is rarer to find an initiative that invests in human capital by attempting to empower energy users. The procedure for such programs is to provide energy users with information and expect them to use their rationality and decision-making power to curb waste consumption, or at least allocate consumption more efficiently. What results is a win-win scenario where the energy user sees a lower utility bill and society sees reduced impacts as a result of reduced consumption.

Such programs are difficult to understand for several reasons. The most obvious of these is the human element; participants in such programs have many different psychological motivations and face numerous contextual obstacles to reduction. These obstacles can manifest themselves in many forms however the one that we choose to focus on is low income. Low income can limit the potential for reduction in several ways. It is possible that energy use may be so low that there is little to shave off, and what there is to reduce is too important to quality of life. Or, as is the case with many low-income households, there are many occupants with conflicting agendas that make coordination difficult if not impossible. The list goes on and on.

However there are also several reasons to believe that low-income households provide an opportunity for reduction. Residents in such households feel the financial pinch of a high utility bill more acutely than many other potential participants as their utility bill forms a much larger percentage of their overall income. They may therefore wish to reduce more than a typical household, but simply lack the information necessary to spur them to action.

1.2 LITERATURE REVIEW

We conducted a literature review in order to better define the scope of our project and put its methodology and results in perspective. Examining residential energy use is nothing new. Literature abounds on the subject, especially in the context of concerns about its environmental impacts. However this perspective often considers only the aggregate; many modeling efforts and analyses are very high level views that examine the aggregate residential consumption of entire countries or regions. It is a smaller subset of literature that focuses on residential energy use at the household level.

The field of literature on household energy consumption often focuses on the role of various demographic factors in determining energy use. Numerous studies examine households by household makeup, gender of household head, and income among other factors (O'Neill and Chen, 2002). However the literature becomes sparser when focusing on low-income households. There are several exceptional papers; we are particularly indebted Parker et al for their 1996 study of low-income households in Florida and their cooling habits, as well as a remarkable analysis by Brandon and Lewis in 1999 that conducted a feedback experiment on residential energy consumption by households in Bath, UK. We choose to expand on the Parker et al study by examining electricity usage in a larger sample of households, and on the Brandon and Lewis study by focusing on low-income households and examining the effect of multiple types of education.

As mentioned before, energy modeling of individual households is but a subset of the literature. This is no wonder, as it is a very difficult problem. Single building models generally fail to predict household energy usage with any real degree of accuracy. In fact, outcome and expectation for individual household models can vary by 80-100% (Lutzenhiser et al, 2010). The reasons for this variance are numerous and some of them are not common among other modeling efforts. All models make certain assumptions and account for some variables while treating others as black boxes however understanding residential energy use requires not only engineering intuition but psychological insights. There are numerous behavioral factors that must be accounted for, some of which defy rational explanation. Many of these factors cannot be explained by economics or even as products of conscious choice rather they are dictated by social and technical structures, personal histories, and cultural interpretations (Lutzenhiser et al, 2010). People may use thermostats in a certain way simply out of habit, rather than rational decision-making, or lighting may be overemployed due to misunderstandings of individual bulb efficacy. Internal temperature preference may be a product of a resident's childhood home. Some take these possibilities to mean that there is not even a single model form that could be reasonably applied to all households.

Despite these problems, there has still been significant effort towards modeling individual households' energy use. There are general theories that can still be applied, largely following a combination of the laws of economics and heat transfer. In one example of theory informing analysis, Henley and Peirson (1997) apply economics to householders' preferences for thermal comfort level (indoor temperature). Combined with the fact that there are thermal limits on heating systems' capabilities, this leads them to believe that there is a nonlinear relationship between indoor temperature and energy consumption. They compare several different model structures and find different order polynomials to be appropriate for different times of the day. We considered a nonlinear approach however rejected it due to scope and data limitations.

Another interesting observation informed by economics is the so-called 'takeback' effect. Milne and Boardman (2001) explain this as a byproduct of the income effect. Residents who receive energy efficiency improvements will increase their residual income by reducing their utility bill. The resulting increase in residual income can be applied to other energy-intensive activities, both direct usage of more energy in the household for other appliances or on other consumer goods that require energy input. However Nadel (1994) concludes that takeback is not a significant factor in households in the United States.

Other observations focus on the demographic aspects of households to provide theoretical backing to studies. With regards to the number and composition of household occupants, there has been extensive study. Fritzche (1981) compares households of different age makeups and comments that households with older children may use less energy as older children spend less time at home. Ritchie et al (1981) examine a large sample of Canadian households and observe variance in energy usage as family size changes. O'Neil and Chen (2002) find this to also be the case on a per capita basis. They conduct a similar analysis and attribute the variance to the correlation between higher household occupancy and lower income or more children (who use less energy on a per-capita basis). Age of household members is another interesting demographic of study with O'Neil and Chen showing per capita energy consumption increasing with age until a person reaches their mid-80s. One final demographic characteristic that has been particularly contentious is the gender of the household head. Klausner (1979) argued that female-headed households are inherently less energy efficient for psychological reasons. However DeFronzo and Warkov (1979) countered this hypothesis with their study of Texas households. They observe no significant difference between male and female-headed households.

Turning now to the role of income, there are further relationships worth exploring. Income is particularly interesting because it will likely impact a person's flexibility to reduce consumption more than many other demographic criteria and would thus have an important interaction effect with energy efficiency education. A key theoretical insight comes from Henley and Peirson (1997) who predict that an energy user's level of thermal comfort, and thus their expenditure for cooling and heating, will vary by income. Ritchie et al (1981) note that work patterns can affect energy expenditure on space conditioning, as those working longer hours have the option to shut heating or cooling systems off when they are not home.

A very insightful study by Parker et al (1996) takes an in-depth look at low-income households' cooling habits. This is of particular importance because households in warm climates will spend a large fraction of their energy expenditure on cooling alone, with Parker et al calculating it to be between 44% and 61% of energy expenditures for their sample. Furthermore, their study involved identical households with identical cooling systems and virtually identical energy efficiency parameters. Therefore the variance they observe, which was significant, stems entirely from demographic and behavioral traits. They note that differing thermostat strategies likely account for a good deal of the variance with some participants being more informed than others about efficient methods of operation.

Finally, we return to the analysis that is most similar to our efforts: that of Brandon and Lewis (1999). Their study provided energy feedback reports to experiment participants in an effort to reduce their consumption. They find that the feedback reports resulted in significant energy usage reduction, and that environmental attitudes had no statistically significant effect on the magnitude of energy reductions post-feedback. Furthermore, they note that income and other socio-demographic variables influence energy usage prior to the feedback effort. However the results indicate that socio-demographic variables had little impact on the magnitude of the feedback's effect.

Chapter 2: Foundation Communities and the Saving Green Program

The Saving Green Program (SGP) is an initiative of Foundation Communities (FC), a nationally recognized non-profit organization that provides affordable homes and support services for over 2,500 low-income families and individuals in the Austin area. Foundation Communities' mission statement is to create housing where families succeed. The core areas of focus are: ownership and operation of sixteen multi-family properties, offering on-site educational programs for adults and children, and providing financial education programs for residents.

SGP started in the spring of 2010 as part of the financial education programs available for FC residents. The impetus for the program's development is a study performed by Foundation Communities staff and Austin Energy that analyzed household energy usage at comparable apartment units. The study found that units of similar household size, floor plans, and structural energy-efficiency could have drastically different energy usage trends throughout the year. In some cases a family would have an electricity bill more than three times larger than a similarly sized family in a similarly sized unit. Through a better understanding of the underlying drivers of these differences build into an educational program, SGP intends to help residents use their units more efficiently and save on their utility bills.

The implementation of SGP consists of a marketing phase, three interactive resident workshops, in-home educational energy audits, and an energy saving contest. The program rotates to a different apartment complex every month. There are three two-hour workshops in the evenings that take place once a week over a three week period. The topics of the workshops are energy and water conservation, reducing transportation costs, and healthy and affordable grocery shopping. Each workshop includes a presentation and interactive "stations" relevant to the main topic. The energy and water conservation workshop stations teach residents about the benefits of compact fluorescent light bulbs, how to limit phantom loads, how to conserve water, and how to read their utility bill.

The in-home energy visits are optional and take place soon after the energy and water conservation workshop. During the visits the SGP coordinator and an experienced energy audit crew perform simple weatherization upgrades, such as adding weather stripping to doors and gaskets behind outlets, and reiterate some of the topics taught in the energy and water workshop. For example, the SGP coordinator will help the resident identify potential phantom loads and check the refrigerator temperature to make sure it is in the proper range. Perhaps the most crucial part of the in-home visit is instruction in how to operate a programmable thermostat.

The majority of the thermostats are Honeywell SuperStat units installed free of charge as part of Austin Energy's Power Saver Program. The program coordinator found that over 90% of the thermostats were either not programmed, improperly programmed, or were set to "hold" a certain temperature to avoid enabling the program. Participants received instruction in programming their thermostat during the audit. Some chose to use the "hold" function to keep their dwelling at a single set temperature, primarily because they were either at home during the day or because they maintained irregular work schedules.

SGP participants received energy reports delivered to their doors. These reports detail electricity and water consumption over the last utility billing period, and show how it compares to past-usage. This is usually the last component of SGP and participants are expected to use this information to better manage their utility bills going forward.

Foundation Communities has completed SGP at seven of the sixteen properties so far. Program coordinators also conducted the program in Spanish at certain properties in order to accommodate Spanish-only speaking households.

Chapter 3: Participant Background

3.1 HOUSEHOLD MAKEUP

In this chapter we conduct an analysis of participants to better understand their context. This includes both understanding what may influence their energy use, and what their energy use looks like at a high level. The goal is to better characterize the communities that are the target of this effort in order inform future efforts.

Our study contains data from fifty one participants of varying household compositions. In this chapter we provide some descriptive statistics about the participants in our sample. The average occupancy rate is 3.04 residents per participant household. However we note that 26% of the participant households are a single occupant and the average occupancy for households with multiple residents is 3.74 people. Furthermore, of the participant households with single occupancy, ten of the twelve are single women. Of participant households with a single occupant, the average birth year is 1944, making the average age of these residents about sixty six at the time of SGP.

Participant households contained many children. We define children as having been born in 1992 or later. 60% of participant households have at least one child and 45% have at least two. 48% of participant households with children are single mothers. All but one of the other participant households with children contains at least one male and one female adult. 11% of participant households have three or more adults. The average birth year of all adults in participant households containing children is 1962, making the average age for said adults about forty eight at the time of the program. Segregating by language, we observe that the Spanish-speaking participant households contain an average of 2.13 children per household and the English-speaking households contain 1.03 children per household.

Analyzing income data reveals more. The average household income of participants in 2009-2010 was $26,864 per year. The average per capita income among all participant households is $12,365 per year. This number diverges greatly when segregated by language of program participation. Participants in the English-speaking program have an average household income of $29,554 per year and an average per capita household income of $15,183 per year. Participants in the Spanish-speaking program earn an average of $21,125 per year and $6,356 per year per capita on average.

We take away several key lessons from examining these demographics. First, there is a tremendous diversity in these communities. There are many single occupants, and almost all of these are older women. However the participant households that do not fall into this category almost all contain children. There are usually multiple children in Spanish-speaking participant households. Income is generally low, although that is a sampling issue and the main reason why we chose this community. We note that on a per-capita basis income in Spanish-speaking participant households is less than half that of English-speaking participant households, although this has in part to do with the large number of children in Spanish-speaking participant households.

3.2 ENERGY USAGE ANALYSIS

We also examine participants' electricity usage patterns in order to better understand opportunities for improvement. We analyze data beginning in November 2008 and ending in September 2011 (although some participants' data starts later or ends sooner, and we take care to only use data from after the current occupant moved into the residence; on average we have 27 months of data for each participant). First, we look at participants' usage in each month, averaged across all years of our sample. We remove participants who do not have at least one available data point available for all twelve calendar months, leaving us with forty five households for this part of the analysis.

First, we note that the average household in this community consumes an average of 7,141 kWh per year. We show a density distribution of participant households' average annual usage in Figure 3.1.

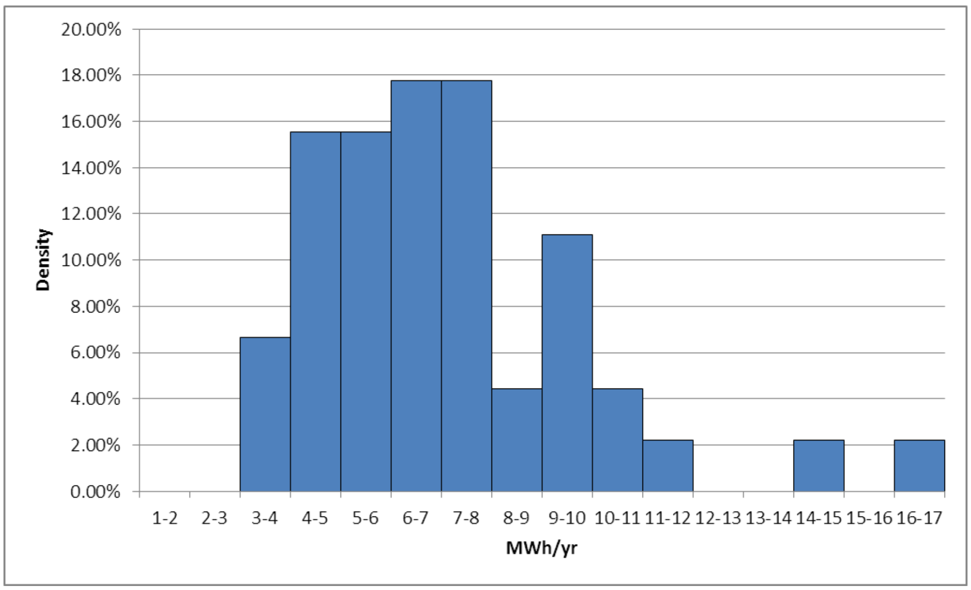

Figure 3.1: Density plot of participants' annual electricity consumption (MWh per year).

The resulting plot is roughly lognormal, with a long tail to the right. No house uses less than 3 MWh per year, and 90% use below about 10 MWh per year. Usage peaks in July, where participants average 30.15 kWh per day of consumption, while it hits its minimum in March where they consume only 13.29 kWh per day.

We then conduct a common sizing, where we measure each participant household's average usage in each month as a percentage of the sum of the averages of usage in all months. The results tell us about the seasonal allocation of electricity, and give some hints about how much goes to cooling versus other uses. Figure 3.2 shows a scatter plot of each participant household's usage in each month as a percentage of their entire expected annual usage.

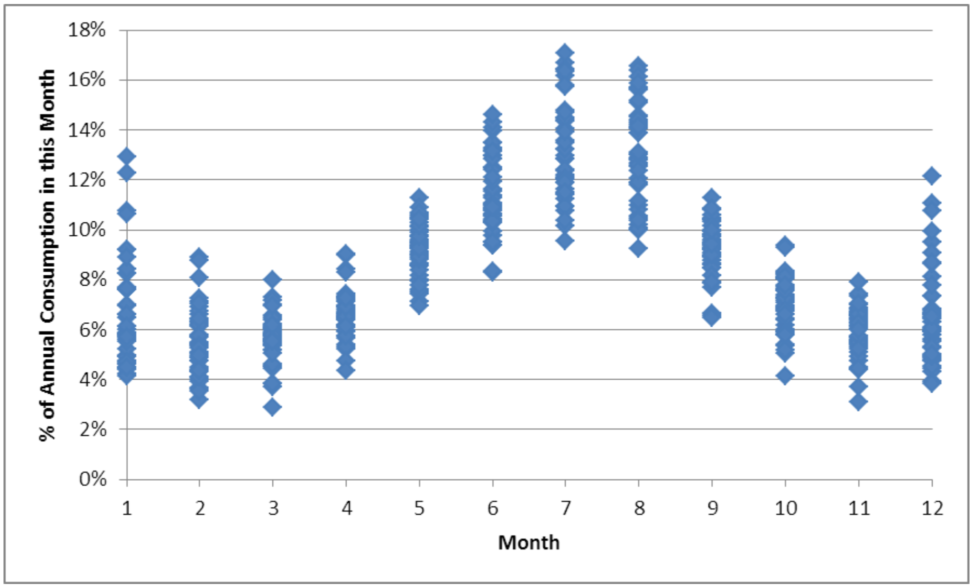

Figure 3.2: Scatter plot of each participant's average percentage allocation of annual electricity consumption to each month.

As one would expect, there is enormous seasonal variation. Because of the intense heat during summers in central Texas, summer usage at peak is more than double the usage minimum in March. The six months we count as summer (May- October) end up accounting for 63% of total annual usage.

We can split up our participant group to learn more, as we show in Table 3.1.

	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
Total	6.5	6.0	5.5	6.7	9.0	11.6	13.0	12.9	9.4	6.9	6.0	6.5
Gas Heat	4.9	4.7	4.9	6.6	9.5	13.1	14.7	14.7	10.0	6.7	5.2	5.1
e- Heat	7.5	6.8	5.9	6.8	8.7	10.7	11.9	11.7	9.1	7.0	6.5	7.3
English	5.9	5.5	5.5	6.8	9.2	12.0	13.4	13.3	9.6	7.0	5.9	6.0
Spanish	8.0	7.0	5.6	6.6	8.7	10.8	12.0	12.0	9.0	6.7	6.2	7.5
Children	6.9	6.2	5.6	6.7	8.9	11.4	12.7	12.6	9.5	6.8	6.0	6.7
No Child	6.1	5.7	5.4	6.7	9.1	11.9	13.4	13.2	9.4	6.9	6.0	6.1

Table 3.1: Average percentage allocation of annual electricity consumption by participant subgroups.

First, we split the participants by heating (gas or electric). As one would expect, the gas-heated units show a higher percentage of usage in the summer months. Gas-heated units use 10% more of their annual electricity consumption in the summer months than electric-heated units. We can gain further insight by examining the gas heated units in the winter months. For these units, when temperatures reach their minimum, usage should be a close approximation of non-cooling or “fixed” load. We find that usage reaches a minimum in March at 4.7% with January and February very close behind. When multiplying by twelve to reach 365 days, we find that this load would be equivalent to 58% of total annual. Therefore one can say that, on average, cooling load is roughly 42% of the annual load in gas-heated households. Furthermore, we can subtract 4.7% from each month’s percentage value, and divide by the original percentage value in each month to estimate roughly what percentage of monthly load goes to cooling. We show this in Figure 3.3. As one would expect, cooling burden peaks in July and August where it takes up almost two thirds of household usage, on average.

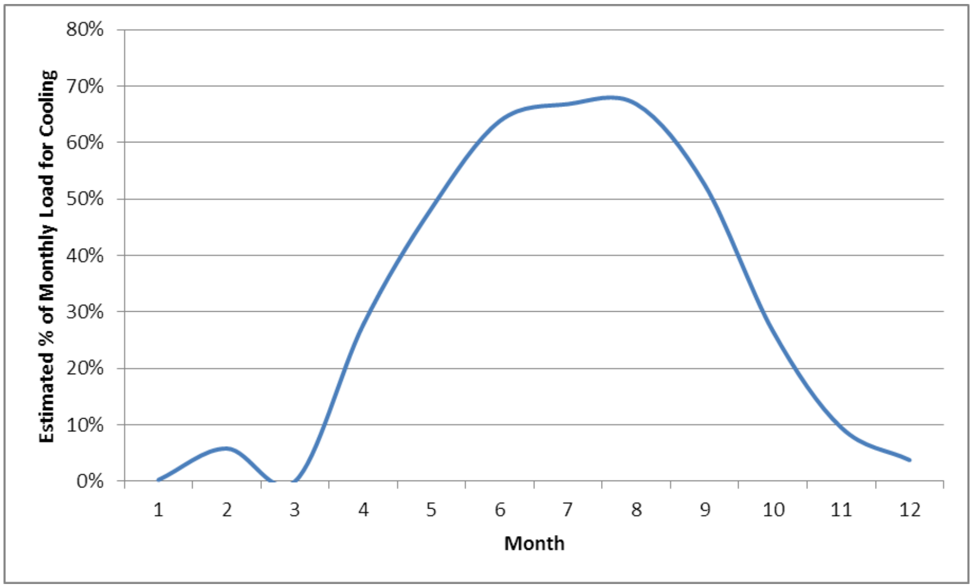

Figure 3.3: Estimate of average monthly load allocated to cooling in gas-heated households.

We also examine the percentage values for other groups as well. We note that Spanish-speaking households appear to devote a larger share of their energy usage to the winter months and less to the summer. This is presumably because of lower cooling load, although the fact that Spanish-speakers are clustered in certain apartment complexes may explain some of the variation. We also differentiate participants by whether or not there are children in the household. We initially hypothesized that households with children might spend more of their usage in the summer due to increased desire for cooling, however the opposite proved to be (mildly) true. Nonetheless, this differentiation appears to show no significant variance and we cannot say that households with children allocate electricity usage differently across months than those without children.

To better understand the interaction between household income and electricity usage, we provide scatter plots of annual household electricity usage as a function of household income in Figure 3.4.

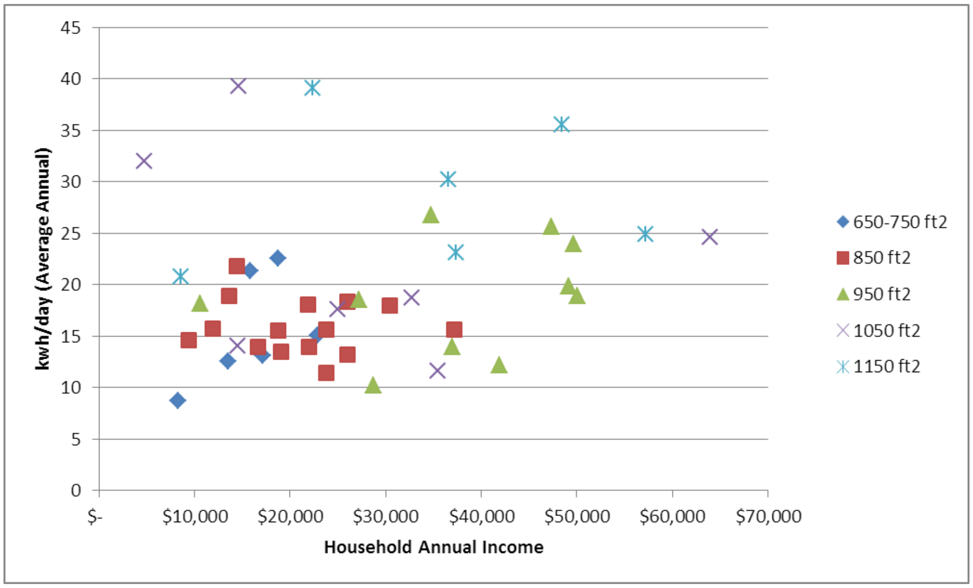

Figure 3.4 Participant average annual usage as a function of income, differentiated by apartment size.

We note that no subset of apartments (by unit size) exhibits a statistically significant relationship against income at any normal confidence level. Furthermore, the group as aggregate exhibits no statistically significant relationship against income. Another key takeaway from this analysis is that most energy users are clustered tightly between about ten and twenty kWh/day. It is only a few outliers that truly separate themselves from the group, and even those are in the largest apartments. This would suggest that the program could benefit from focusing more on these participants.

We also wanted to better understand what the ‘energy burden,’ electricity expenditure divided by income, is for these households. We show a density plot for this in Figure 3.5.

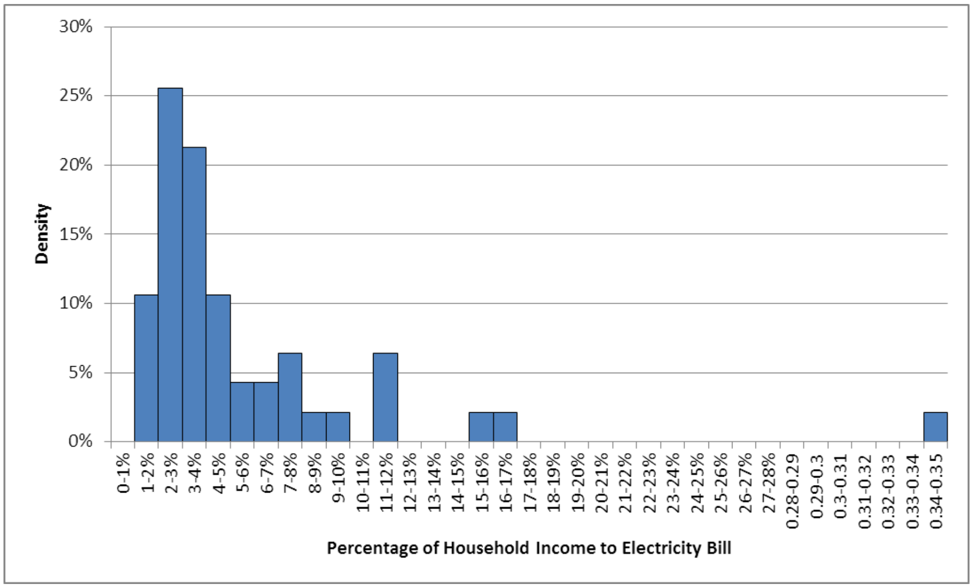

Figure 3.5: Density plot of energy burden (electricity bill / income).

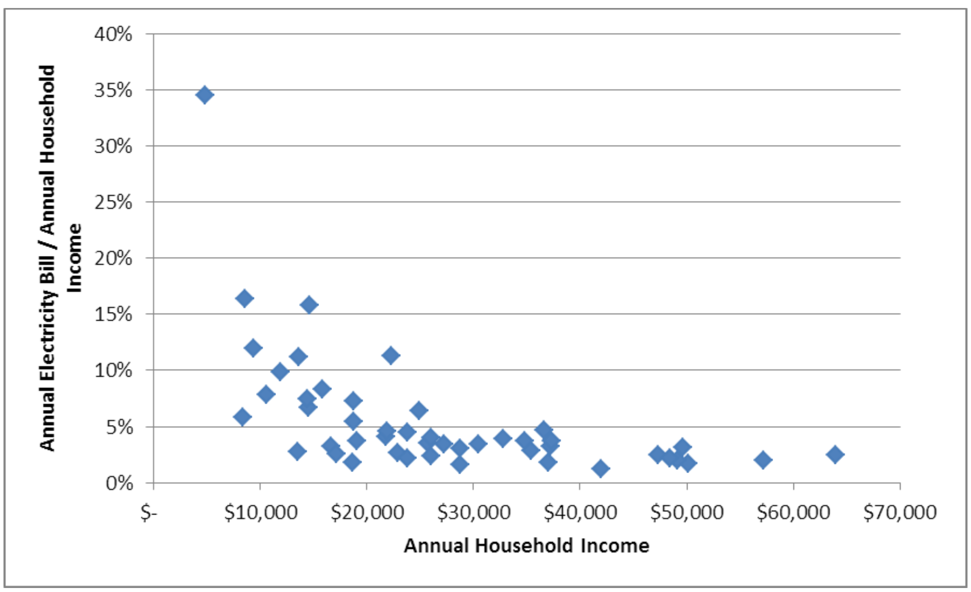

Figure 3.6: Energy burden as a function of household income.

We use the twelve most recent examples of each calendar month and add them to reach what a typical year's worth of billings would look like. For participants missing months due to lack of data, we normalize using available months. The results show that these households spend, on average, 2-4% percent of annual income on electricity. However the distribution has a long tail and we see many households up until about 10%. We also create a scatter plot, Figure 3.6, of energy burden as a function of household income. There is a negative relationship between income and energy burden largely because, as we showed, income and energy usage appear to have no correlation in this sample.

Our examination of participant household energy usage reveals several characteristics of low-income energy use. First, we note that roughly 42% of annual load goes to cooling in gas-heated households. Second, we observe that the percentage of monthly load that goes to cooling peaks at roughly two thirds of monthly load in July and August. We also note that Spanish-speaking households appear to allocate less of their usage to the summer months, presumably due to less use of cooling. However this may also be due to a higher concentration of Spanish-speakers in certain apartment complexes that have a type of structural makeup that lends itself to certain consumption profiles. Households with children appear to show a similar annual profile to those without children. Regarding the relationship between income and energy consumption, we note that there appears to be no relationship between participant income and electricity consumption in this sample. And finally, we see that this contributes to lower-income participant households having a greater percentage of their income going to electricity bills. In total, our analysis of energy usage paints a picture of households where cooling load is a major driver and income plays little role in explaining usage patterns.

Chapter 4: Interviews

We interviewed thirteen SGP participants in order to better understand contextual factors, such as household makeup or job considerations, that may dictate electricity usage patterns. In selecting interviewees, we attempted to produce a group as diverse as possible. Our sample includes participants from all but one complex, those with both gas and electric heating systems, and varying demographic makeups. The goal was to identify any trends that may not bubble to the surface in the quantitative analyses in Chapters 5-6. As mentioned before, household energy usage patterns are not solely the product of engineering systems or easily quantifiable variables. They are in part the product of numerous contextual factors that may or may not be visible in a study based on looking at electricity consumption data.

We asked participants a series of questions related to their recollections of SGP and their attitudes and habits regarding energy use. As we mentioned before, SGP attempts to instruct participants in several ways to reduce energy consumption. However, the point that almost all participants we interviewed hung onto the most was increased plug load awareness. This is one of the points that the energy and water workshop focuses on and is likely the greatest surprise to most participants. Furthermore, it is likely the most attractive reduction option in participants' eyes as existing plug loads are sheer economic loss, compared to cooling which carries value even if it is not optimally managed. Surprisingly, fewer participants seemed to recall any lessons on thermostats with only four out of thirteen mentioning the thermostat in the set of lessons they learned.

In order to better understand contextual issues and background circumstances, we also asked questions regarding obstacles to further conservation or any unusual events that may have taken place during the study. We initially hypothesized that there may be effects competing against SGP that would cause participants to use more energy. Foundation Communities is dedicated to improving the economic standing of its residents. It might then be the case that, as time goes on, participants may increase consumption and purchase devices that increase electricity usage. We found little evidence of this effect. Only three participants claimed to have purchased any new appliances and there is one in each outcome category of our econometric analysis reported in Chapter 6 (statistically significant increase in usage, decrease in usage, and inconclusive). Furthermore, two of these were replacements for older and more inefficient appliances (a refrigerator, and a television) and should actually decrease electricity consumption. Given the aforementioned answers, it is unlikely that economic advancement of participants is diluting SGP's impact.

As a further test of program impact, we asked questions to test awareness of household electricity use. Specifically, what in the household uses the most energy and which of the steps the participant took had the most impact on their electricity usage. Given that the participants all live in central Texas, it would be very unlikely that the correct answer to the former question should be anything but cooling. Consumption data supports this with most participants roughly doubling electricity consumption in July and August relative to the winter minimum. To our surprise the answers to this question were very erratic. Only three participants listed cooling as the greatest use of electricity in their house. Five listed either the refrigerator or the freezer, with the rest listing either television or kitchen appliances. To the second question, what habit undertaken since SGP had the largest impact, only three participants gave an answer involving the thermostat. Interestingly enough, all three of these participants exhibited statistically significant increases in electricity consumption across the program. There may therefore be another gap between awareness of the thermostat as a major load driver and the ability or willingness to act on it. Other answers varied, but generally focused on either plug loads or just turning appliances off more frequently.

Although it appears that thermostat habits were not significantly affected by SGP, we asked participants what their thermostat habits were. Almost all participants claimed to have season-specific strategies. Furthermore, many participants seemed to show a significant tolerance for warmth in the summer with set temperatures approaching eighty degrees. One participant even claimed to rely principally on fans for cooling, although their usage profile appears to show about 10 kwh/day spikes in the peak of the summer heat relative to their minimum usage in the spring and autumn months.

We asked participants what additional information or help they wish to receive, or if they had sought out any additional information to help them conserve energy. While most participants were eager to attend more classes and enjoyed the educational and community aspects of SGP, few had an answer for what else they would like to see or receive and most did not seek additional information. One exception to this was a participant sought out more information about thermostats to the extent that they attended an outside class instructing him on proper usage. Another participant wished for more extensive weatherization, complaining about aluminum window frames' ability to conduct heat. One of the more intrepid participants actually continued to hunt for cracks in their attic that were causing air leakage.

Finally, we asked participants what factors in their life kept them from conserving more. All participants who had an answer (ten out of thirteen) mentioned cohabitants, in most cases children. How children prevented more conservation varied. One woman answered that she preferred to keep it cool for them in the house when they return from playing in the summer heat, while another lamented the electrification of playtime. Another woman repeatedly mentioned how much laundry she does as a result of her children. It appears that there are numerous mechanisms with none standing out especially.

One unexpected note we observed from participants' answers was their readiness and ability to disseminate information. One interviewee gave her neighbors, who did not participate in SGP, some tips on how to save. Others emphasized how they teach their children the lessons they learned and how it is necessary to save electricity given their economic circumstances. Another interviewee was actually not present at the energy and water workshop, but recited what his wife had learned and passed along to him.

We also separated our interviewees by outcome identified in the analysis in Chapter 6 (increase in energy usage, decrease, or inconclusive) in an attempt to identify any patterns. Three of the seven participants we interviewed who showed an increase in usage seem to have extenuating circumstances, specifically a broken window and house guests. While it may be easy to say that this is evidence of the deck being stacked against this program, one must keep in mind that these are simply a product of the environment in such communities. Broken windows will take longer to repair and houseguests with little energy awareness will come and go more often than in higher-income households.

Our interview results show that participants absorbed information about plug loads readily however they struggled to retain information regarding the importance of cooling. We also learned that there might not be that much room for improvement, as thermostats are usually already set to high temperatures or completely off a great deal of the time. This is largely in line with our results articulated in the following chapters which show relatively higher program impact in the winter months. Contextual factors seem to vary among participants. There is no evidence for our initial hypothesis that economic advancement was leading to increased electricity consumption, while cohabitants such as temporary guests or children seem to hinder efforts to conserve.

However there is a silver lining here, as we find anecdotal evidence of information dissemination in the community. All in all, a variety of these factors seem to imply not much flexibility in electricity consumption in these households.

Chapter 5: Participants/Non-Participants Comparison Analysis

5.1 INTRODUCTION

In this chapter we conduct a comparison between program participants and non-participants. The goal is to conduct a substitute for a more rigorous panel data analysis, as non-participant data is only available as the average of non-participants in a given apartment complex for a given apartment size. By comparing participants and non-participants who lived in the same sized units and in the same buildings, we hope to isolate the SGP effect.

5.2 METHODOLOGY

FC provided us with monthly electricity usage data for all program participants' apartments beginning in November 2008, and ending in September 2011. Because disclosure of data requires consent of the occupant, data for non-participants is available only as the average across all non-participants in a given complex and of a given square footage. The absence of non-participant data prevents us from conducting a traditional difference-in-difference panel data regression. We therefore take two other approaches, the first being a comparison between average usage of participants and non-participants.

We begin by averaging monthly usage across all participants within a given complex, and for a given unit size. We only include participants who have at least twelve months of usage data prior to the energy and water workshop, as well as at least one month of data after. This assures that we will be using the same set of participants across all months of our analysis (no participants moved out during our analysis). After removing participants with insufficient data, we are left with forty one participants split into fourteen groups indexed by apartment complex and unit size. We then compare each group's monthly usage to its own usage twelve months prior. We obtain a value for each month that shows, in percentage terms, how a group's average electricity usage changed relative to twelve months before (e.g.: $\frac{kwh_{March\ 2010} - kwh_{March\ 2011}}{kwh_{March\ 2010}}$). We therefore have two tables, one for participants and one for non-participants, that has fourteen columns (groups differentiated by complex or unit size), and twenty two rows for twenty two months across which we have data (note that almost all groups are missing some data at either the start or the end of this twenty two month period). Finally, we construct Table 5.3 by subtracting the non-participant table from the participant table to see if each participant group reduced more energy, on average, in a given month than non-participants.

	Abbreviated Complex Name and Unit Size													
	BU 950	CC 850	CC 950	CC 1150	CR 750	CR 1050	DF 850	SR 650	SR 850	SR 1050	SWT 1050	TP 750	TP 1050	TP 1150
12/09	n/a	-0.7	9.7	n/a	14.5	-8.0	13.0	-195	-3.3	-653	n/a	n/a	n/a	n/a
1/10	10.6	-6.9	-1.7	n/a	12.3	-1.4	3.1	-102	-40.6	-97.2	-3.2	-23.5	-85.5	7.3
2/10	-20.7	-6.8	0.1	n/a	9.1	-23.2	-15.7	-45.1	-27.6	-5.6	-20.4	-18.4	-110.5	11.7
3/10	23.0	-4.2	-1.4	n/a	6.0	-11.5	2.0	-4.7	-3.5	24.3	-19.3	21.9	-90.0	19.8
4/10	9.8	11.3	22.7	n/a	-2.6	-19.8	6.5	16.0	9.4	30.1	17.4	18.5	-85.8	-0.7
5/10	1.7	13.0	20.8	n/a	-21.1	-10.5	-22.2	10.7	6.2	13.9	9.5	17.4	-83.4	-3.9
6/10	2.8	29.0	16.5	n/a	-4.9	-5.0	-23.4	9.7	5.3	-2.4	15.0	7.0	-48.9	0.3
7/10	13.6	32.8	12.5	n/a	-7.9	-5.8	-13.4	11.3	12.8	4.6	4.4	0.3	17.5	-1.1
8/10	3.5	15.2	0.3	13.6	-4.8	-1.6	-36.0	2.0	4.1	-11.8	-1.5	-13.5	16.9	0.5
9/10	3.0	1.7	-1.0	-97.7	-28.1	-27.8	-70.9	-6.7	1.5	-9.9	-15.3	-35.9	-9.7	-3.9
10/10	1.1	-11.4	-20.3	2.6	-18.6	-36.7	-128	-3.7	8.0	4.9	-14.0	-24.5	8.0	-5.4
11/10	3.0	-13.8	-11.2	19.6	-24.4	-47.6	-109	11.7	15.0	19.1	-26.5	-12.6	24.9	-5.4
12/10	19.3	-22.9	2.8	10.1	-10.9	-16.1	-79.4	25.4	25.8	35.3	-31.4	2.4	34.7	2.1
1/11	-6.0	-16.3	-1.9	11.3	-15.4	-12.0	-77.9	12.1	16.4	17.6	-38.5	-0.3	6.9	6.7
2/11	30.4	-2.3	-1.9	13.4	-9.8	4.2	-61.7	8.1	9.2	7.4	-39.1	4.7	19.1	-2.8
3/11	3.8	-25.9	-15.9	-5.2	-11.9	-26.9	-119	19.3	15.4	23.4	-35.8	-6.6	11.3	-0.3
4/11	0.4	-62.6	-31.7	-16.1	-18.8	-63.8	-132	-14.0	-1.1	1.0	-39.4	-11.1	-5.3	-7.7
5/11	19.0	-45.8	-26.3	-9.5	-3.4	-30.7	-36.3	-10.5	-5.3	-6.9	-20.7	-12.3	5.4	8.0
6/11	16.1	-52.9	-14.6	-10.4	1.3	-6.1	-23.7	-9.0	-11.6	-16.1	-4.5	-1.9	8.8	14.9
7/11	-0.1	-67.3	-11.1	-20.1	-0.5	-12.1	-29.1	-14.3	-16.6	-17.4	-8.4	-5.1	20.0	-7.8
8/11	-0.3	-60.5	-13.0	-36.0	-1.4	14.8	-10.6	-27.8	-21.2	-18.6	-0.8	2.8	13.3	-15.7
9/11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-2.6	n/a	n/a	n/a	n/a	n/a

Table 5.1: Percentage reduction in monthly electricity consumption relative to twelve months prior for participants.

	Abbreviated Complex Name and Unit Size													
	BU 950	CC 850	CC 950	CC 1150	CR 750	CR 1050	DF 850	SR 650	SR 850	SR 1050	SWT 1050	TP 750	TP 1050	TP 1150
12/09	n/a	-15.0	9.4	-11.4	-5.8	-3.9	-7.3	-35.5	-16.4	-14.0	n/a	n/a	n/a	n/a
1/10	-5.9	2.0	9.5	-12.3	-9.3	-9.1	-3.4	-43.9	-46.9	-29.5	5.9	-15.3	-8.7	-1.7
2/10	-3.1	13.9	11.1	2.8	-1.3	4.7	10.2	-18.8	-28.5	-9.1	8.3	-7.5	-5.0	-0.7
3/10	17.6	6.1	11.5	3.7	8.6	-0.4	15.3	2.6	-5.5	11.6	5.6	10.8	10.2	8.8
4/10	9.4	7.0	15.9	12.5	7.5	-4.4	10.0	10.0	4.7	13.3	7.2	-5.5	11.7	-2.1
5/10	6.4	-1.7	9.0	4.7	-0.7	-10.8	2.2	4.0	0.6	4.4	-0.5	-10.6	5.9	-5.8
6/10	15.1	4.9	16.8	9.2	7.9	6.5	6.3	6.1	1.3	8.8	6.6	-0.8	7.4	3.9
7/10	16.3	6.9	16.9	8.3	9.2	6.5	9.8	11.6	5.8	9.6	2.0	-0.7	7.1	9.3
8/10	0.3	-1.2	5.6	1.9	0.4	-1.3	-4.0	5.1	-1.3	2.8	-5.5	-4.0	0.6	-1.3
9/10	-7.3	-4.3	2.5	1.2	-12.3	-17.9	-10.8	1.4	-1.0	-1.5	-11.0	-8.4	-6.2	-8.8
10/10	-2.5	-12.4	-11.4	-13.6	-18.6	-17.3	-52.3	-1.4	-4.6	-1.5	-11.2	-15.3	-11.3	-12.5
11/10	2.5	-5.7	-15.4	-14.3	-7.7	8.9	-0.7	7.9	-0.8	8.4	-10.6	-1.0	-1.4	-10.6
12/10	9.9	1.6	-9.0	-4.1	-7.0	2.6	-3.2	17.9	12.7	19.8	-5.6	3.5	4.3	-7.4
1/11	9.6	-7.5	-15.1	-6.5	-0.7	4.3	-5.9	2.1	1.1	6.3	-7.6	4.5	0.3	-0.8
2/11	3.6	-10.2	-13.3	-3.8	-6.3	-11.5	-18.4	0.6	-4.6	0.2	-8.0	-8.0	-4.6	-4.3
3/11	-16.0	-15.6	-29.0	-15.3	-25.1	-21.5	-19.6	11.5	5.3	3.2	-15.7	-29.4	-20.8	-18.2
4/11	-23.1	-21.2	-33.7	-21.1	-35.7	-21.8	-33.0	-14.5	-16.3	-16.5	-17.1	-33.3	-31.1	-25.9
5/11	5.5	-8.2	-16.6	-11.4	-4.3	-1.0	-4.2	-11.8	-12.2	-9.1	-4.3	-10.9	-11.0	-7.5
6/11	-0.9	-15.7	-15.8	-16.3	-6.0	-7.9	0.3	-10.1	-13.4	-7.1	-4.8	-3.3	-6.9	-11.2
7/11	-6.6	-14.6	-18.2	-16.7	-12.2	-17.4	-3.6	-11.4	-14.2	-6.4	-3.1	-5.5	-10.3	-20.2
8/11	-0.3	-18.8	-15.8	-19.5	-7.1	-8.6	1.5	-19.9	-16.9	-12.6	1.2	-13.3	-8.0	-13.0
9/11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-21.8	-6.9	n/a	n/a	n/a	n/a	n/a

Table 5.2: Percentage reduction in monthly electricity consumption relative to twelve months prior for non-participants.

	Abbreviated Complex Name and Unit Size													
	BU 950	CC 850	CC 950	CC 1150	CR 750	CR 1050	DF 850	SR 650	SR 850	SR 1050	SWT 1050	TP 750	TP 1050	TP 1150
12/09	n/a	14.3	0.2	n/a	20.4	-4.1	20.4	-159	13.1	-638.5	n/a	n/a	n/a	n/a
1/10	16.5	-8.9	-11.3	n/a	21.6	7.7	6.5	-57.7	6.3	-67.7	-9.1	-8.2	-76.8	9.1
2/10	-17.5	-20.7	-11.1	n/a	10.3	-27.9	-26.0	-26.3	0.9	3.5	-28.7	-10.8	-105.5	12.4
3/10	5.4	-10.3	-12.8	n/a	-2.5	-11.1	-13.4	-7.3	2.0	12.7	-24.9	11.2	-100.2	11.0
4/10	0.5	4.3	6.9	n/a	-10.1	-15.4	-3.5	5.9	4.7	16.8	10.2	24.0	-97.5	1.5
5/10	-4.6	14.7	11.9	n/a	-20.4	0.3	-24.3	6.7	5.6	9.5	10.1	28.0	-89.4	1.8
6/10	-12.3	24.2	-0.3	n/a	-12.8	-11.5	-29.7	3.6	4.1	-11.3	8.5	7.9	-56.3	-3.6
7/10	-2.7	25.9	-4.5	n/a	-17.0	-12.3	-23.2	-0.3	7.0	-5.0	2.4	1.0	10.3	-10.4
8/10	3.3	16.4	-5.3	11.7	-5.2	-0.3	-32.0	-3.1	5.4	-14.6	4.0	-9.5	16.3	1.8
9/10	10.3	6.1	-3.5	-98.8	-15.8	-9.9	-60.1	-8.1	2.4	-8.4	-4.3	-27.5	-3.5	4.9
10/10	3.5	1.0	-8.9	16.2	0.0	-19.4	-75.1	-2.3	12.6	6.4	-2.8	-9.2	19.3	7.1
11/10	0.5	-8.1	4.2	33.8	-16.8	-56.4	-108	3.8	15.8	10.7	-15.8	-11.5	26.3	5.2
12/10	9.4	-24.6	11.8	14.2	-3.9	-18.7	-76.2	7.5	13.1	15.5	-25.9	-1.1	30.5	9.5
1/11	-15.5	-8.8	13.2	17.8	-14.7	-16.3	-71.9	10.0	15.3	11.2	-31.0	-4.9	6.6	7.5
2/11	26.8	8.0	11.4	17.2	-3.5	15.7	-43.3	7.5	13.7	7.2	-31.1	12.7	23.8	1.6
3/11	19.8	-10.4	13.1	10.2	13.2	-5.3	-99.0	7.8	10.0	20.2	-20.1	22.8	32.1	17.9
4/11	23.5	-41.4	2.0	5.0	16.9	-42.0	-99.1	0.5	15.2	17.5	-22.3	22.2	25.9	18.2
5/11	13.5	-37.6	-9.7	1.9	0.9	-29.7	-32.1	1.3	6.9	2.2	-16.4	-1.4	16.4	15.5
6/11	17.1	-37.2	1.3	6.0	7.2	1.8	-24.0	1.1	1.8	-9.0	0.4	1.4	15.7	26.1
7/11	6.6	-52.8	7.0	-3.4	11.7	5.2	-25.5	-3.0	-2.5	-10.9	-5.3	0.4	30.3	12.5
8/11	0.0	-41.8	2.8	-16.5	5.7	23.4	-12.2	-7.8	-4.3	-6.1	-2.0	16.1	21.4	-2.6
9/11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	4.3	n/a	n/a	n/a	n/a	n/a

Table 5.3: Difference in electricity consumption reduction between participants and non-participants (participants - non-participants).

A positive value in Table 5.3 indicates a greater reduction in electricity usage (relative to twelve months before) by that subgroup (complex and unit size) of participants in that month than non-participants in that month. The border line for each subgroup shows the month when SGP's energy and water workshop occurred for that subgroup.

We only examine months that occur after the workshop, as this was our cutoff for twelve months of continuity in group makeup and any month prior would be invalid due to changes in the participants who make up the group. Furthermore, only the months after are relevant to measuring program effectiveness. This analysis seems to indicate that within most subgroups, the program was largely successful. We find the average value after the workshop for each participant group and show it in Table 5.4, along with a count of how many months the participants reduced more than the same group of non-participants and how many months the participants reduced less than the same group of non-participants.

		BU 950	CC 850	CC 950	CC 1150	CR 750	CR 1050	DF 850	SR 650	SR 850	SR 1050	SWT 1050	TP 750	TP 1050	TP 1150
All	Avg. After	13%	-23%	4%	9%	8%	-8%	-19%	2%	8%	5%	-11%	10%	24%	15%
69.64%	Part. Win	6	2	9	9	5	3	0	8	11	8	1	5	6	5
	Part. Lose	0	9	2	2	0	2	2	4	2	4	5	1	0	1
Summer	Avg. After	9%	-34%	-2%	1%	6%	0%	-19%	-3%	3%	-4%	-4%	8%	26%	5%
59.38%	Part. Win	4	1	3	3	4	3	0	2	5	2	1	3	4	3
	Part. Lose	0	4	2	2	0	1	2	4	2	4	3	1	0	1
Winter	Avg. After	22%	-14%	9%	16%	17%	-42%	n/a	6%	14%	14%	-21%	22%	29%	18%
83.33%	Part. Win	2	1	6	6	1	0	n/a	6	6	6	0	2	2	2
	Part. Lose	0	5	0	0	0	1	n/a	0	0	0	2	0	0	0

Table 5.4: Participant performance comapred to non-participants with percentage of occurances where participants outperform non-participants.

5.3 RESULTS

Of the fourteen groups, ten of them show average values greater than zero (i.e.: lower comparative electricity consumption) across all months after the workshop. Furthermore, eleven of the fourteen participant groups reduced more than their corresponding non-participant group in most months. In total, there are 112 months of data after the workshop when adding all fourteen groups together. Participants showed more reduction than non-participants in seventy eight of the months, or 70% of the time.

When we split the results seasonally, they vary slightly. In the summer, only eight of fourteen groups showed more average energy use reduction in the participants than the non-participants. However eleven of the fourteen groups showed more months where participants reduced more than non-participants than where participants reduced less than non-participants. In total, of sixty four months of summer data across all groups, participants reduced more than non-participants thirty eight times, or 59% of the time.

Data for the winter is sparser and we lose one group due to absence of winter data from after the program. Of the thirteen groups for which data is available, ten showed higher average reduction for participants than non-participants. The very same ten also showed more months where the participants outperformed the non-participants. In total, of forty eight months across all groups after the workshop, participants reduced more than non-participants forty times, or 83% of the time.

We also conduct a statistical test to see if the values after SGP are lower than the values before. That is, did each subgroup of participants' performance relative to non-participants increase after SGP. This allows us to account for the possibility that something makes participant subgroups more likely to conserve in general other than SGP. We report the results in Table 5.5

	BU 950	CC 850	CC 950	CC 1150	CR 750	CR 1050	DF 850	SR 650	SR 850	SR 1050	SWT 1050	TP 750	TP 1050	TP 1150
All	3.28	-5.97	2.86	n/a	2.23	0.50	0.94	1.88	2.47	1.38	-0.43	1.77	2.48	3.93
Summer	2.47	-22.46	-0.03	n/a	4.69	2.38	1.43	-3.11	-6.55	-0.69	-3.04	0.60	1.69	3.95
Winter	2.46	-1.79	4.19	n/a	1.18	-1.34	n/a	2.16	4.26	1.40	-0.32	2.43	1.66	3.83

Table: 5.5: Z-test of participant performace against non-participant performance comparing before and after SGP.

We lose some subgroups due to insufficient data (at least two months of data from both before and after SGP are required). However in the analysis of all months, we note that five out of thirteen subgroups showed a statistically significant improvement in performance (reduced more compared to non-participants after the workshop than before) from before to after SGP at the 99% confidence level. Only one participant subgroup showed a statistically significant worsening in performance. When we segregate by season, the results come into focus. In the summer, four out of thirteen participant subgroups showed an improvement in performance while four also showed worse performance. In the winter, five participant subgroups showed an improvement in performance while none showed worse performance. This analysis seems to indicate that the program may have had some effect for some subgroups, and the winter months appear to have a more pronounced difference from before to after SGP.

Our percentage change analysis allows us to perform a very high-level difference-in-difference approach as a substitute for a more sophisticated panel data analysis. The results indicate that there is some evidence of program impact. If there were no impact, we would expect participants and non-participants to show roughly comparable performance across all months after the workshop. Furthermore, we note the striking difference in seasonal performance. It appears that participants performed only marginally better than non-participants in the summer. However in the winter they reduced more than non-participants 83% of the time. This seems to indicate that any gains that were made were likely made in areas other than cooling load. This is consistent with what we learned in the interviews in Chapter 4, namely that participants had difficulty grasping the importance of or exhibit any flexibility with cooling load, however they managed to reduce some fixed load including plug loads.

Chapter 6: Comparison Against Own Past-Usage

6.1 INTRODUCTION

In this chapter we compare each participant household's electricity consumption from after SGP's various events to their own electricity consumption from before the start of SGP. The goal is to create a model of each participant household's monthly electricity consumption, and see if monthly electricity consumption exhibited a statistically significant change from before to after SGP while accounting for changes in temperature that would otherwise bias the results.

6.2 METHODOLOGY

We begin this analysis by assuming that climatic variation (change in temperature) is the key determinant of household electricity consumption. Changes in temperature will affect any before-after analysis. If we do not control for temperature, it is easy to misestimate the impact of SGP. We therefore begin by specifying a model of household electricity consumption as a function of temperature:

$$E_{a,i} = F_{a,i} + \alpha_{a,i}(T_a - C_{a,i}) \qquad (1)$$

$$E_{b,i} = F_{b,i} + \alpha_{b,i}(T_b - C_{b,i}) \qquad (2)$$

Where equation (1) defines average daily electricity usage by a participant household in a single month before (*b*) an intervention (energy and water workshop, energy report, energy visit, or all events a participant undertook in entirety), and equation (2) defines average daily electricity use after (*a*) an intervention. E is participant household electricity consumption in kWh per day averaged across the entire month indexed by participant (i) and time (b for months occurring before the intervention, and a for months occurring after the intervention). The interventions we consider are the program components explained in Chapter 2: the energy and water workshop, the energy report, the in-home energy visit, and the entire duration of the program participated in by each participant. F represents fixed participant household energy consumption that is not affected by temperature, for example, lighting and household appliance use. We assume that it is time invariant (i.e.: usage of lighting and appliances does not vary across calendar months) within set a and within set b.

The bracketed term beginning with α represents energy consumption that varies with outside temperature, or more specifically: cooling and heating load. Some models of household energy consumption assume a linear relationship between energy consumption and the difference between inside and outside temperature (at least within certain ranges) due to the laws of heat transfer and mechanical properties of cooling systems. We follow this line of thinking by defining energy usage as a linear function of the difference between average monthly outside temperature, T, and a participant-specific parameter that represents internal temperature preferences, C. We scale this difference by α, which is a measure of overall household system efficiency with regards to maintaining internal temperature. If $\alpha>0$, a lower internal temperature preference will result in more electricity consumption. If $\alpha<0$, a higher internal temperature preference will result in more electricity consumption.

We find that we can calculate α values for each participant using our existing temperature and electricity usage data. Consider subtracting the energy usage of one month (2) from another (1), assuming that they are both within either set a or set b:

$$\Delta E_i = E_{1,i} - E_{2,i} = F_{1,i} - F_{2,i} + \alpha_i\left(T_1 - C_{1,i}\right) - \alpha_i\left(T_2 - C_{1,i}\right) \quad (3)$$

We assume that α is time-invariant within set a or set b and we eliminate index a/b for simplicity. Furthermore, we assume that non-heating or cooling load, F, is time invariant within set a or set b. Therefore $F_{1,i}=F_{2,i}$. Finally, we assume that internal temperature preference, C, is time invariant within set a or set b. Therefore $C_{1,i}=C_{2,i}$. The reasoning for this is that there are unlikely to be any events other than SGP in our timeframe that would cause C to change (note that we also split the analysis by season later, so variations would have to occur within the summer or within the winter, it is acceptable for them to happen inter-seasonally). That is, there is unlikely to be any reason for participants to significantly change their thermostat set temperatures other than SGP itself. We can reduce equation (3) to:

$$\Delta E_i = \alpha_i(T_1 - T_2) = \alpha_i \Delta T \qquad (4)$$

Because we observe E and T, α is the only missing component and we can calculate it using electricity usage and temperature data. We also note that we have many data points and instead of simple subtraction we use an OLS regression approach to find a best-fit value for α given many observed ΔE and ΔT values (we can generate one observation given any combination of two months within set a and set b of usage and temperature data). However we take note of a model limitation here. α is likely to vary across seasons. In the summer, cooling load dominates and one would expect a positive relationship between energy and outside temperature. Therefore we expect $\alpha>0$ in summer (defined as May through October). In the winter, cooling load is less prominent and heating load would likely play a role. Therefore we expect $\alpha<0$ in winter (defined as November through April). Because of this complication we must calculate seasonal α values. Furthermore, equation (4) only holds if C is time invariant. For reasons we explain later in this section, we believe that C may change from before an intervention to after. We must therefore calculate intervention segregated α values (one α for before an intervention, eg: energy and water workshop, and another α for after an intervention). We therefore consider four α values for each participant in a given intervention: one calculated using summer months before an intervention, one calculated using summer months after the intervention, one calculated using winter months before the intervention, and one calculated using winter months after the intervention. As a data-enhancing simplification, we only consider the energy and water workshop as an intervention in calculating α values. We do this because using other interventions that occur later (energy report, in-home energy visit) as a before-after breakpoint results in insufficient quantities of data in the set of 'after' months.

We now wish to consider the effect of the program by comparing household electricity consumption before an intervention to household electricity consumption after an intervention. We specify the following:

$$\Delta E_i^0 = E_{a,i} - E_{b,i} \qquad (5)$$

where b is the index of all months occurring before an intervention, and a is the index of all months occurring after an intervention. We now assume that $\alpha_{a,i} = \alpha_{b,i}$ (we choose to index α by p going forward, as there are four α values to choose from for each participant) . This amounts to saying that overall household system efficiency did not change from before to after an intervention. Subtracting equation (2) from (1), we arrive at the following:

$$\Delta E_i^0 = E_{a,i} - E_{b,i} = \left(F_{a,i} - F_{b,i}\right) + \alpha_{p,i}(T_a - T_b) + \alpha_{p,i}\left(C_{b,i} - C_{a,i}\right) \qquad (6)$$

At this point we assume $F_{a,i}$=$F_{b,i}$. This implies that SGP will have a minimal effect on load that does not come as a result of cooling or heating. The program includes several aspects that attempt to do this, including but not limited to CFL light replacement and plug load awareness. However, we believe this effect is negligible compared to its impact on cooling and heating load and it is necessary for our method of temperature control. We can now reduce equation (6) to:

$$\Delta E_i^0 = \alpha_{p,i}(T_a - T_b) + \alpha_{p,i}\left(C_{b,i} - C_{a,i}\right) \qquad (7)$$

Recall that C represents a participant's internal temperature preference. Due to our assumption of $F_{a,i}$=$F_{b,i}$, the only method a participant has to reduce electricity consumption is through changing *C*. Behavior creating reduction in energy use would be raising it when cooling load is a major driver and $\alpha>0$, or lowering it when electrical resistance heating load is significant and $\alpha<0$. The hypothesis we test is therefore:

$$D = \Delta E_i^0 - \alpha_{p,i}\left(T_{a,i} - T_{b,i}\right) = \alpha_{p,i}\left(C_{b,i} - C_{a,i}\right) \qquad (8)$$
$$(H): \overline{D_{p,\iota}} = 0$$

Note that the first line of equation (8) is simply a manipulation of equation (7). We perform this manipulation because *C* is not observed. We have no data on participants' thermostat set temperatures. However, in equation (8), we note that we can calculate an equivalent value using temperature and energy data which we do observe and α which we calculate using these observations and equation (4).

We calculate a D value for every combination of one month before (b) an intervention with one month after (a) an intervention. However, as mentioned in the discussion of calculating α, we segregate the analysis by season and by before/after the intervention. So we calculate four different sets of D values (summer before, summer after, winter before, winter after) for each participant for each intervention analysis (four interventions leads to sixteen $\overline{D_{p,\iota}}$ values for each participant).

For example, if a participant had the energy and water workshop occur on August 1, 2010 and we had household usage data from March 2010 to December 2010, we would calculate nine summer D values (May, June, and July 2010 against August, September, and October 2010) and four winter D values (March and April 2010 against November and December 2010). We would calculate each set twice using an α value calculated with the before data (May through July for summer, and March through April for winter) and an α value calculated with the after data (August through October for summer, and November through December for winter). Therefore there would be two summer sets each containing nine D values, and two winter sets each containing four D values. This whole process would be repeated with the August 1 benchmark shifted to match the dates of each intervention, with the entire program excluding all months between the first and last components of SGP to occur for the participants.

We average all D values within a set indexed by p to arrive at $\overline{D_{p,\iota}}$. We define energy usage reduction as $\overline{D_{p,\iota}}<0$, and energy usage increase as $\overline{D_{p,\iota}}>0$. Because we assume α is nonzero this is equivalent to defining reduction as $C_{b,i}-C_{a,i}<0$ (internal temperature preference rose) and increase as $C_{b,i}-C_{a,i}>0$ (internal temperature preference fell) when α>0. The opposite is the case when α<0.

Using the $\overline{D_{p,i}}$ value calculated for each participant in each of the sixteen statistical tests, we calculate a t-statistic for each participant in each test using equation (9).

$$t_{p,i} = \frac{\overline{D_{p,i}}}{\sigma_{p,i} / \sqrt{N_{p,i}}} \qquad (9)$$

where σ is the standard deviation of all *D* values for a participant and *N* is the number of *D* values we calculate in a given test. Again, recall that a $t_{p,i}$ above the critical value (2.33 at a 99% confidence interval) implies increase in energy usage, while a $t_{p,i}$ below the negative of the critical value implies decrease in energy usage. Therefore a highly positive *t* is indicative of increases in energy use from before to after the program, while a highly negative *t* is indicative of decreases in energy use from before compared to after the program.

6.3 RESULTS

Tables 6.1-6.3 show the results of the statistical tests we describe in the regression model summary for all four interventions. We note α, $\overline{D}$, and t-statistic for each participant. We also break down the participants' outcomes (at the 99% confidence level) by key variables available to us in Tables 6.4-6.5, specifically whether they participated in an English workshop or a Spanish workshop, and whether they have electric or gas heating. We further break down outcomes by each apartment complex in Table 6.6.

Table 6.1: α values for participants in all seasons (kwh/day*F).

	E&W				ER				EV				ALL			
	Winter		Summer		Winter		Summer		Winter		Summer		Winter		Summer	
SGID	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A
1	-0.05	0.17	0.92	0.78	-0.04	0.16	0.83	0.89	-0.05	0.17	0.92	0.78	-0.05	0.16	0.92	0.89
2	-0.16	0.04	1.21	1.65	-0.16	0.16	1.24	1.41	-0.16	0.04	1.22	1.65	-0.16	0.16	1.21	1.41
3	0.01	0.15	0.62	0.81	0.01	0.24	0.65	0.40	0.01	0.15	0.63	0.81	0.01	0.24	0.62	0.40
4	0.17	0.18	0.85	1.17	0.17	0.32	0.77	0.86	0.17	0.18	0.83	1.17	0.17	0.32	0.85	0.86
7	-0.18	0.01	0.93	0.74	-0.10	n/a	0.93	2.23	-0.18	0.01	0.93	0.74	-0.18	n/a	0.93	2.23
11	n/a	0.24	n/a	0.92	0.24	n/a	n/a	1.11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1.11
13	0.19	0.28	0.93	0.47	0.22	n/a	0.93	-0.22	0.19	0.28	0.93	0.47	0.19	n/a	0.93	-0.22
17	-0.20	0.00	0.38	0.49	-0.20	0.00	0.38	0.50	-0.20	0.00	0.38	0.58	-0.20	0.00	0.38	0.50
19	0.16	0.04	-0.03	0.35	0.16	0.04	0.06	0.22	0.16	0.04	-0.03	0.35	0.16	0.04	-0.03	0.22
23	-0.16	-0.01	0.40	0.50	-0.16	-0.01	0.40	0.33	-0.16	-0.01	0.40	0.56	-0.16	-0.01	0.40	0.33
31	-0.59	-0.47	0.54	0.62	-0.59	-0.47	0.52	0.59	-0.59	-0.47	0.54	0.62	-0.59	-0.47	0.54	0.59
35	-0.27	-0.23	0.62	0.64	-0.27	-0.23	0.59	0.69	-0.27	-0.23	0.62	0.64	-0.27	-0.23	0.62	0.69
42	0.09	0.04	0.40	0.52	0.09	0.04	0.45	0.47	0.09	0.04	0.40	0.54	0.09	0.04	0.40	0.47
44	-0.20	-0.15	0.37	0.40	-0.20	-0.15	0.36	0.35	-0.20	-0.15	0.37	0.42	-0.20	-0.15	0.37	0.35
47	-0.21	-0.23	0.13	0.29	-0.21	-0.23	0.13	0.28	-0.21	-0.23	0.13	0.29	-0.21	-0.23	0.13	0.28
54	-0.07	-0.22	0.51	0.77	-0.07	-0.22	0.57	0.77	-0.07	-0.22	0.51	0.77	-0.07	-0.22	0.51	0.77
58	-0.54	-0.52	0.51	0.46	-0.54	-0.52	0.46	0.54	-0.54	-0.52	0.51	0.46	-0.54	-0.52	0.51	0.54
63	0.03	0.01	0.39	0.47	0.03	0.01	0.40	0.43	0.03	0.01	0.39	0.47	0.03	0.01	0.39	0.43
70	-0.37	-0.34	0.53	0.46	-0.37	-0.34	0.51	0.48	-0.37	-0.34	0.53	0.46	-0.37	-0.34	0.53	0.48
73	-0.31	-0.25	0.46	0.45	-0.31	-0.25	0.45	0.58	-0.31	-0.25	0.46	0.45	-0.31	-0.25	0.46	0.58
74	-0.48	-0.15	0.60	0.73	-0.48	-0.15	0.61	0.35	-0.48	-0.15	0.64	0.71	-0.48	-0.15	0.60	0.35
76	-0.59	-0.52	0.49	0.49	-0.59	-0.52	0.46	0.54	-0.59	-0.52	0.51	0.50	-0.59	-0.52	0.49	0.54
78	-0.02	n/a	n/a	0.84	0.53	n/a	n/a	2.58	n/a	n/a	n/a	n/a	-0.02	n/a	n/a	2.58
79	0.01	n/a	0.63	0.66	0.06	n/a	0.63	0.65	n/a	n/a	n/a	n/a	0.01	n/a	0.63	0.65
80	0.15	n/a	0.67	0.30	0.11	n/a	0.67	0.43	n/a	n/a	n/a	n/a	0.15	n/a	0.67	0.43
81	0.56	n/a	0.61	0.67	0.58	n/a	0.61	-1.41	n/a	n/a	n/a	n/a	0.56	n/a	0.61	-1.41
82	-0.14	n/a	0.51	0.23	-0.11	n/a	0.51	2.18	-0.14	n/a	0.51	0.23	-0.14	n/a	0.51	2.18
83	-0.12	n/a	0.42	0.26	-0.15	n/a	0.42	3.03	-0.12	n/a	0.42	0.26	-0.12	n/a	0.42	3.03
85	-0.01	n/a	n/a	0.60	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
89	-0.05	n/a	1.11	1.31	0.03	n/a	1.11	1.53	-0.05	n/a	1.11	1.31	-0.05	n/a	1.11	1.53
90	-0.31	n/a	0.73	0.29	-0.13	n/a	0.73	-2.35	-0.31	n/a	0.73	0.29	-0.31	n/a	0.73	-2.35
93	-0.02	0.02	0.63	0.76	-0.02	0.05	0.65	0.49	-0.02	0.02	0.63	0.76	-0.02	0.05	0.63	0.49
95	n/a	n/a	n/a	0.28	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.28	n/a	n/a	n/a	n/a
96	0.21	n/a	n/a	0.21	0.07	n/a	n/a	n/a	0.01	n/a	n/a	0.21	0.21	n/a	n/a	n/a
97	0.00	n/a	0.80	0.75	0.08	n/a	0.76	n/a	0.00	n/a	0.80	0.75	0.00	n/a	0.80	n/a
100	0.00	n/a	0.37	0.28	0.01	n/a	0.35	n/a	0.00	n/a	0.37	0.28	0.00	n/a	0.37	n/a
101	n/a	n/a	n/a	0.96	0.45	n/a	n/a	n/a	0.38	n/a	n/a	0.96	n/a	n/a	n/a	n/a
102	0.67	n/a	0.14	0.52	0.69	n/a	0.63	n/a	n/a	n/a	n/a	n/a	0.67	n/a	0.14	n/a
105	0.00	n/a	1.05	0.86	0.11	n/a	1.05	1.75	n/a	n/a	n/a	n/a	0.00	n/a	1.05	1.75
106	0.15	n/a	1.20	0.76	0.22	n/a	1.20	1.19	n/a	n/a	n/a	n/a	0.15	n/a	1.20	1.19
108	-0.09	n/a	0.89	1.31	-0.20	n/a	0.89	1.11	-0.09	n/a	0.89	1.31	-0.09	n/a	0.89	1.11
117	0.21	n/a	0.78	0.77	0.21	n/a	0.99	n/a	n/a	n/a	n/a	n/a	0.21	n/a	0.78	n/a

Table 6.1 (continued)

118	0.27	n/a	0.56	0.65	0.27	n/a	0.40	n/a	0.27	n/a	0.56	n/a	0.27	n/a	0.56	n/a
119	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
125	0.05	0.11	0.99	0.39	0.06	0.12	0.92	0.91	0.05	0.11	0.98	0.39	0.05	0.12	0.99	0.91
126	0.31	0.15	2.06	0.78	0.29	0.17	2.08	0.83	0.31	0.15	2.08	0.78	0.31	0.17	2.06	0.83
127	0.03	0.33	1.18	1.26	0.04	0.40	1.16	1.01	n/a	n/a	n/a	n/a	0.03	0.40	1.18	1.01
128	0.04	0.13	0.68	0.96	0.04	0.21	0.65	0.74	0.04	0.13	0.67	0.96	0.04	0.21	0.68	0.74
129	0.25	0.24	1.12	1.42	0.24	0.31	1.21	1.18	n/a	n/a	n/a	n/a	0.25	0.31	1.12	1.18
131	n/a	0.35	0.81	1.22	n/a	0.40	1.02	1.00	n/a	0.35	1.04	1.22	n/a	0.40	0.81	1.00
132	0.16	0.28	1.24	1.54	0.15	0.43	1.32	1.16	0.16	0.28	1.29	1.54	0.16	0.43	1.24	1.16

Table 6.2: $\overline{\mathrm{D}}$ values for participants in all seasons.

	E&W				ER				EV				ALL			
	Winter		Summer		Winter		Summer		Winter		Summer		Winter		Summer	
SGID	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A
1	0.67	0.10	1.69	1.88	0.39	-0.33	1.61	1.28	0.67	0.10	1.81	2.03	0.60	-0.21	1.29	1.41
2	-1.61	-2.15	3.12	2.54	-1.29	-2.43	5.29	4.36	-1.61	-2.15	3.50	2.83	-1.41	-2.68	4.78	3.93
3	0.36	0.07	1.53	1.27	1.19	0.51	2.80	4.20	0.36	0.07	1.77	1.49	1.06	0.32	2.53	3.51
4	5.98	5.95	10.01	9.59	7.09	6.36	11.06	10.55	5.98	5.95	9.68	9.16	7.30	6.41	11.33	11.29
7	7.11	5.17	3.58	4.71	n/a	n/a	3.73	-7.50	7.11	5.17	3.58	4.71	n/a	n/a	3.73	-7.50
11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
13	3.46	2.75	-5.16	-2.64	n/a	n/a	-6.86	2.85	3.46	2.75	-5.16	-2.64	n/a	n/a	-6.86	2.85
17	-1.93	-2.50	1.85	1.61	-1.93	-2.50	2.68	2.03	-1.93	-2.50	2.16	1.89	-1.93	-2.50	2.83	2.22
19	-4.12	-3.81	-0.66	-1.47	-4.12	-3.81	1.28	0.40	-4.12	-3.81	-0.75	-1.27	-4.12	-3.81	1.05	-0.23
23	-1.66	-1.92	0.59	0.38	-1.66	-1.92	2.11	2.50	-1.66	-1.92	0.91	0.69	-1.66	-1.92	1.87	2.19
31	0.82	0.50	0.35	0.15	0.82	0.50	0.01	-0.04	0.82	0.50	0.35	0.15	0.82	0.50	0.17	0.09
35	2.50	2.39	2.26	2.22	2.50	2.39	4.41	3.86	2.50	2.39	2.26	2.22	2.50	2.39	4.18	3.82
42	-3.25	-3.13	-2.37	-2.62	-3.25	-3.13	-2.83	-2.96	-3.25	-3.13	-2.66	-2.85	-3.25	-3.13	-2.96	-3.32
44	0.39	0.25	-0.07	-0.13	0.39	0.25	0.69	0.74	0.39	0.25	0.12	0.05	0.39	0.25	0.43	0.55
47	-1.70	-1.63	-0.96	-2.02	-1.70	-1.63	-1.20	-1.64	-1.70	-1.63	-0.96	-2.02	-1.70	-1.63	-1.24	-2.14
54	-1.06	-0.65	1.32	0.77	-1.06	-0.65	2.35	1.29	-1.06	-0.65	1.32	0.77	-1.06	-0.65	2.59	1.31
58	0.34	0.29	0.02	0.12	0.34	0.29	1.27	0.85	0.34	0.29	0.02	0.12	0.34	0.29	0.78	0.61
63	-1.92	-1.87	-2.40	-2.59	-1.92	-1.87	-0.89	-1.08	-1.92	-1.87	-2.40	-2.59	-1.92	-1.87	-1.67	-1.90
70	0.54	0.46	-0.40	-0.25	0.54	0.46	-1.14	-0.98	0.54	0.46	-0.40	-0.25	0.54	0.46	-1.10	-0.87
73	2.19	2.04	0.55	0.59	2.19	2.04	1.52	0.66	2.19	2.04	0.55	0.59	2.19	2.04	1.28	0.55
74	3.86	2.95	5.51	5.20	3.86	2.95	7.46	8.83	3.86	2.95	5.70	5.61	3.86	2.95	8.36	9.69
76	-0.93	-1.12	0.33	0.31	-0.93	-1.12	1.27	0.85	-0.93	-1.12	0.38	0.40	-0.93	-1.12	1.01	0.74
78	12.16	n/a	n/a	14.17	n/a	n/a	n/a	-16.61	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-16.61
79	1.50	n/a	0.80	0.63	n/a	n/a	0.89	0.70	n/a	n/a	n/a	n/a	n/a	n/a	0.89	0.70
80	-1.50	n/a	-1.97	0.08	n/a	n/a	-3.00	-0.97	n/a	n/a	n/a	n/a	n/a	n/a	-3.00	-0.97
81	1.76	n/a	-1.39	-1.69	n/a	n/a	-2.30	14.69	n/a	n/a	n/a	n/a	n/a	n/a	-2.30	14.69
82	1.20	n/a	-1.97	-0.46	n/a	n/a	-1.81	-15.85	1.20	n/a	-1.97	-0.46	n/a	n/a	-1.81	-15.85
83	-2.86	n/a	-3.79	-2.93	n/a	n/a	-2.90	-24.88	-2.86	n/a	-3.79	-2.93	n/a	n/a	-2.90	-24.88
85	3.48	n/a	n/a	1.68	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
89	3.43	n/a	3.06	1.97	n/a	n/a	3.74	0.21	3.43	n/a	3.06	1.97	n/a	n/a	3.74	0.21
90	2.48	n/a	-11.81	-9.23	n/a	n/a	-14.41	12.27	2.48	n/a	-11.81	-9.23	n/a	n/a	-14.41	12.27
93	-1.01	-1.17	-0.67	-0.84	-0.70	-1.08	0.55	1.44	-1.01	-1.17	-0.42	-0.63	-0.92	-1.34	0.08	0.67
95	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
96	-2.61	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1.92	n/a	n/a	n/a	n/a	n/a	n/a	n/a
97	6.77	n/a	-0.33	-0.03	n/a	n/a	-1.70	n/a	6.58	n/a	-0.33	-0.03	n/a	n/a	-1.88	n/a
100	1.29	n/a	-0.15	0.32	n/a	n/a	-0.23	n/a	1.28	n/a	-0.15	0.32	n/a	n/a	-0.39	n/a
101	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1.73	n/a	n/a	n/a	n/a	n/a	n/a	n/a
102	1.16	n/a	16.92	14.94	n/a	n/a	8.71	n/a	n/a	n/a	n/a	n/a	n/a	n/a	17.72	n/a
105	3.81	n/a	-1.42	-0.41	n/a	n/a	-1.51	-7.42	n/a	n/a	n/a	n/a	n/a	n/a	-1.51	-7.42
106	1.66	n/a	-4.02	-1.45	n/a	n/a	-5.10	-5.03	n/a	n/a	n/a	n/a	n/a	n/a	-5.10	-5.03
108	-5.61	n/a	-8.46	-10.86	n/a	n/a	-7.36	-9.23	-5.61	n/a	-8.46	-10.86	n/a	n/a	-7.36	-9.23
117	n/a	n/a	13.14	13.28	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Table 6.2 (continued)

118	n/a	n/a	-4.86	-5.61	n/a	n/a	n/a	n/a	n/a	n/a	-4.73	n/a	n/a	n/a	n/a	n/a
119	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
125	2.15	2.00	-5.19	-4.39	1.64	1.43	-7.58	-7.51	2.15	2.00	-5.32	-4.41	1.92	1.64	-7.49	-7.13
126	-1.80	-1.41	-14.40	-12.70	-1.18	-0.81	-18.27	-11.44	-1.80	-1.41	-14.33	-12.34	-1.53	-1.03	-18.21	-12.81
127	4.52	3.71	3.35	3.25	4.07	2.81	3.81	4.66	n/a	n/a	n/a	n/a	4.52	3.09	3.83	4.60
128	1.52	1.27	3.86	3.48	1.73	1.10	5.19	4.68	1.52	1.27	3.94	3.49	1.76	1.07	4.92	4.65
129	-1.51	-1.49	0.80	0.41	-0.75	-0.98	1.68	1.85	n/a	n/a	n/a	n/a	-1.08	-1.28	1.71	1.47
131	n/a	n/a	5.20	5.18	n/a	0.55	5.82	5.94	n/a	n/a	5.04	4.90	n/a	n/a	6.80	6.22
132	-1.75	-2.34	3.86	3.17	-1.43	-2.87	5.10	6.16	-1.75	-2.34	4.07	3.45	-1.92	-3.54	5.20	5.60

Table 6.3: T-statistic values for all participants in all seasons.

	E&W				ER				EV				ALL			
	Winter		Summer		Winter		Summer		Winter		Summer		Winter		Summer	
SGID	B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A
1	2.13	0.30	3.59	3.71	1.00	-0.90	3.30	2.71	2.13	0.30	4.17	4.31	1.48	-0.54	2.47	2.66
2	-3.07	-4.15	4.87	4.37	-1.89	-3.27	11.25	9.74	-3.07	-4.15	5.68	5.19	-1.95	-3.41	9.48	7.90
3	1.25	0.28	3.81	2.99	3.27	1.47	8.54	11.52	1.25	0.28	4.56	3.66	2.85	0.88	7.80	10.34
4	13.07	13.12	22.45	22.36	19.53	20.48	33.63	31.71	13.07	13.12	20.92	20.97	18.64	18.29	41.69	41.64
7	7.67	5.88	5.75	6.64	n/a	n/a	4.83	-4.25	7.67	5.88	5.75	6.64	n/a	n/a	4.83	-4.25
11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
13	6.80	5.45	-7.96	-4.55	n/a	n/a	-11.18	2.21	6.80	5.45	-7.96	-4.55	n/a	n/a	-11.18	2.21
17	-4.99	-7.54	6.67	6.41	-4.99	-7.54	9.16	7.76	-4.99	-7.54	7.34	7.34	-4.99	-7.54	8.09	7.19
19	-7.77	-7.26	-1.40	-3.61	-7.77	-7.26	2.88	0.99	-7.77	-7.26	-1.40	-2.91	-7.77	-7.26	1.96	-0.48
23	-3.91	-4.83	1.85	1.26	-3.91	-4.83	6.77	7.18	-3.91	-4.83	2.65	2.31	-3.91	-4.83	4.94	5.31
31	1.49	0.92	1.70	0.71	1.49	0.92	0.03	-0.20	1.49	0.92	1.70	0.71	1.49	0.92	0.84	0.46
35	7.48	7.37	7.12	7.09	7.48	7.37	29.66	21.17	7.48	7.37	7.12	7.09	7.48	7.37	24.50	19.07
42	-22.66	-21.95	-13.28	-13.32	-22.66	-21.95	-16.68	-18.05	-22.66	-21.95	-15.05	-12.65	-22.66	-21.95	-18.34	-22.89
44	1.10	0.72	-0.39	-0.74	1.10	0.72	3.14	3.30	1.10	0.72	0.60	0.29	1.10	0.72	1.69	2.04
47	-5.32	-5.10	-1.99	-3.78	-5.32	-5.10	-3.10	-3.86	-5.32	-5.10	-1.99	-3.78	-5.32	-5.10	-2.21	-3.49
54	-1.64	-1.01	3.91	2.54	-1.64	-1.01	8.17	4.41	-1.64	-1.01	3.91	2.54	-1.64	-1.01	7.01	3.43
58	0.67	0.56	0.11	0.60	0.67	0.56	7.02	4.67	0.67	0.56	0.11	0.60	0.67	0.56	4.07	3.18
63	-9.46	-9.03	-9.36	-10.66	-9.46	-9.03	-2.81	-3.46	-9.46	-9.03	-9.36	-10.66	-9.46	-9.03	-5.38	-6.26
70	1.25	1.06	-1.80	-1.18	1.25	1.06	-5.75	-4.99	1.25	1.06	-1.80	-1.18	1.25	1.06	-4.25	-3.36
73	6.57	6.37	2.37	2.50	6.57	6.37	5.61	1.98	6.57	6.37	2.37	2.50	6.57	6.37	4.02	1.43
74	6.79	5.89	11.30	10.91	6.79	5.89	15.47	15.02	6.79	5.89	10.15	10.43	6.79	5.89	15.16	14.03
76	-1.74	-2.12	1.67	1.62	-1.74	-2.12	7.02	4.67	-1.74	-2.12	2.13	2.17	-1.74	-2.12	4.88	3.55
78	7.99	n/a	n/a	7.16	n/a	n/a	n/a	-20.78	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-20.78
79	3.03	n/a	2.31	1.76	n/a	n/a	2.21	1.72	n/a	n/a	n/a	n/a	n/a	n/a	2.21	1.72
80	-3.50	n/a	-4.56	0.18	n/a	n/a	-7.32	-2.08	n/a	n/a	n/a	n/a	n/a	n/a	-7.32	-2.08
81	3.83	n/a	-1.58	-1.88	n/a	n/a	-2.11	6.15	n/a	n/a	n/a	n/a	n/a	n/a	-2.11	6.15
82	3.62	n/a	-4.47	-0.75	n/a	n/a	-3.12	-8.68	3.62	n/a	-4.47	-0.75	n/a	n/a	-3.12	-8.68
83	-4.76	n/a	-3.21	-2.35	n/a	n/a	-2.02	-8.33	-4.76	n/a	-3.21	-2.35	n/a	n/a	-2.02	-8.33
85	2.71	n/a	n/a	0.52	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
89	5.53	n/a	4.97	3.09	n/a	n/a	5.35	0.24	5.53	n/a	4.97	3.09	n/a	n/a	5.35	0.24
90	1.83	n/a	-9.21	-7.85	n/a	n/a	-10.56	3.04	1.83	n/a	-9.21	-7.85	n/a	n/a	-10.56	3.04
93	-4.96	-5.60	-1.54	-2.00	-2.58	-3.57	1.46	3.26	-4.96	-5.60	-1.02	-1.61	-3.29	-4.28	0.20	1.53
95	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
96	-9.23	n/a	n/a	n/a	n/a	n/a	n/a	n/a	6.67	n/a	n/a	n/a	n/a	n/a	n/a	n/a
97	23.63	n/a	-0.48	-0.05	n/a	n/a	-1.57	n/a	23.27	n/a	-0.48	-0.05	n/a	n/a	-1.58	n/a
100	10.66	n/a	-0.86	1.85	n/a	n/a	-1.09	n/a	11.35	n/a	-0.86	1.85	n/a	n/a	-1.60	n/a
101	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	2.46	n/a	n/a	n/a	n/a	n/a	n/a	n/a
102	3.21	n/a	26.47	21.49	n/a	n/a	4.01	n/a	n/a	n/a	n/a	n/a	n/a	n/a	19.11	n/a
105	4.39	n/a	-4.08	-0.99	n/a	n/a	-3.60	-8.64	n/a	n/a	n/a	n/a	n/a	n/a	-3.60	-8.64
106	3.44	n/a	-5.87	-1.98	n/a	n/a	-7.77	-7.68	n/a	n/a	n/a	n/a	n/a	n/a	-7.77	-7.68
108	-5.33	n/a	-13.37	-15.45	n/a	n/a	-12.50	-13.92	-5.33	n/a	-13.37	-15.45	n/a	n/a	-12.50	-13.92
117	n/a	n/a	18.70	18.97	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Table 6.3 (continued)

118	n/a	n/a	-13.38	-15.36	n/a	n/a	n/a	n/a	n/a	n/a	-10.55	n/a	n/a	n/a	n/a	n/a
119	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
125	11.21	10.10	-5.59	-4.67	6.12	5.19	-12.00	-11.89	11.21	10.10	-6.17	-5.11	7.31	6.02	-10.20	-9.64
126	-3.36	-2.61	-9.96	-9.64	-1.94	-1.37	-17.97	-8.79	-3.36	-2.61	-10.40	-10.22	-2.29	-1.60	-15.96	-8.95
127	8.05	6.78	5.03	4.85	5.67	4.16	6.23	7.55	n/a	n/a	n/a	n/a	6.00	4.28	5.21	6.22
128	7.60	7.02	9.11	8.15	6.53	4.06	18.22	16.51	7.60	7.02	9.84	8.93	6.33	3.68	14.85	13.78
129	-6.37	-6.23	1.49	0.66	-2.52	-3.20	3.32	3.72	n/a	n/a	n/a	n/a	-3.80	-4.33	3.16	2.62
131	n/a	n/a	5.35	10.29	n/a	0.82	14.46	14.57	n/a	n/a	9.46	11.46	n/a	n/a	9.08	10.85
132	-3.34	-4.28	3.42	2.85	-2.15	-3.58	5.55	6.63	-3.34	-4.28	4.11	3.50	-2.76	-4.22	4.46	4.77

COUNT		EW				ER				EV				ALL			
		Winter		Summer		Winter		Summer		Winter		Summer		Winter		Summer	
		B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A
ENGLISH	Decrease	11	7	10	8	4	6	10	10	8	6	7	8	5	6	9	10
	Inconclusive	4	3	9	12	5	5	7	6	4	3	6	5	4	4	9	7
	Increase	17	6	11	12	5	4	13	12	11	5	9	9	5	4	12	11
SPANISH	Decrease	4	4	3	3	4	4	3	3	4	4	3	2	4	4	3	3
	Inconclusive	5	5	5	5	5	5	0	1	5	5	4	5	5	5	1	2
	Increase	3	3	6	6	3	3	9	8	3	3	6	5	3	3	8	7
PERCENT																	
ENGLISH	Decrease	34%	44%	33%	25%	29%	40%	33%	36%	35%	43%	32%	36%	36%	43%	30%	36%
	Inconclusive	13%	19%	30%	38%	36%	33%	23%	21%	17%	21%	27%	23%	29%	29%	30%	25%
	Increase	53%	38%	37%	38%	36%	27%	43%	43%	48%	36%	41%	41%	36%	29%	40%	39%
SPANISH	Decrease	33%	33%	21%	21%	33%	33%	25%	25%	33%	33%	23%	17%	33%	33%	25%	25%
	Inconclusive	42%	42%	36%	36%	42%	42%	0%	8%	42%	42%	31%	42%	42%	42%	8%	17%
	Increase	25%	25%	43%	43%	25%	25%	75%	67%	25%	25%	46%	42%	25%	25%	67%	58%
SPREAD																	
ENG-SPAN	Decrease	1%	10%	12%	4%	-5%	7%	8%	11%	1%	10%	9%	20%	2%	10%	5%	11%
	Inconclusive	-29%	-23%	-6%	2%	-6%	-8%	23%	13%	-24%	-20%	-3%	-19%	-13%	-13%	22%	8%
	Increase	28%	13%	-6%	-5%	11%	2%	-32%	-24%	23%	11%	-5%	-1%	11%	4%	-27%	-19%

Table 6.4: Breakdown of outcomes by language subgroup.

COUNT		EW				ER				EV				ALL			
		Winter		Summer		Winter		Summer		Winter		Summer		Winter		Summer	
		B	A	B	A	B	A	B	A	B	A	B	A	B	A	B	A
ELECTRIC	Decrease	9	6	7	7	6	6	8	8	7	6	6	7	6	6	7	8
	Inconclusive	7	6	12	13	6	6	6	7	7	6	9	9	6	6	9	8
	Increase	14	5	8	9	3	3	13	10	11	5	8	7	3	3	11	9
GAS	Decrease	6	5	6	4	2	4	5	5	5	4	4	3	3	4	5	5
	Inconclusive	2	2	2	4	4	4	1	0	2	2	1	1	3	3	1	1
	Increase	6	4	9	9	5	4	9	10	3	3	7	7	5	4	9	9
PERCENT																	
ELECTRIC	Decrease	30%	35%	26%	24%	40%	40%	30%	32%	28%	35%	26%	30%	40%	40%	26%	32%
	Inconclusive	23%	35%	44%	45%	40%	40%	22%	28%	28%	35%	39%	39%	40%	40%	33%	32%
	Increase	47%	29%	30%	31%	20%	20%	48%	40%	44%	29%	35%	30%	20%	20%	41%	36%
GAS	Decrease	43%	45%	35%	24%	18%	33%	33%	33%	50%	44%	33%	27%	27%	36%	33%	33%
	Inconclusive	14%	18%	12%	24%	36%	33%	7%	0%	20%	22%	8%	9%	27%	27%	7%	7%
	Increase	43%	36%	53%	53%	45%	33%	60%	67%	30%	33%	58%	64%	45%	36%	60%	60%
SPREAD																	
ELECTRIC	Decrease	-13%	-10%	-9%	1%	22%	7%	-4%	-1%	-22%	-9%	-7%	3%	13%	4%	-7%	-1%
- GAS	Inconclusive	9%	17%	33%	21%	4%	7%	16%	28%	8%	13%	31%	30%	13%	13%	27%	25%
	Increase	4%	-7%	-23%	-22%	-25%	-13%	-12%	-27%	14%	-4%	-24%	-33%	-25%	-16%	-19%	-24%

Table 6.5: Breakdown of outcomes by heating system subgroup.

COUNT		EW				ER				EV				ALL			
COMPLEX	OUTCOME	Winter		Summer		Winter		Summer		Winter		Summer		Winter		Summer	
BU	Decrease	1	0	3	1	0	0	3	3	1	0	1	1	0	0	3	3
BU	Inconclusive	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
BU	Increase	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CC	Decrease	5	5	2	2	2	4	2	2	4	4	2	2	3	4	2	2
CC	Inconclusive	2	2	2	2	4	4	1	0	2	2	1	1	3	3	1	1
CC	Increase	4	4	8	8	5	4	9	10	3	3	7	7	5	4	9	9
CR	Decrease	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CR	Inconclusive	0	0	2	2	0	0	2	0	0	0	2	2	0	0	2	0
CR	Increase	3	0	1	1	0	0	1	0	4	0	0	0	0	0	1	0
DF	Decrease	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0
DF	Inconclusive	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DF	Increase	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
SR	Decrease	6	6	2	4	6	6	4	4	6	6	2	4	6	6	3	4
SR	Inconclusive	6	6	8	6	6	6	1	3	6	6	7	6	6	6	4	4
SR	Increase	3	3	5	5	3	3	10	8	3	3	6	5	3	3	8	7
SWT	Decrease	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SWT	Inconclusive	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SWT	Increase	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TP	Decrease	2	0	4	2	0	0	3	3	1	0	3	2	0	0	3	3
TP	Inconclusive	1	0	2	5	0	0	3	3	1	0	0	1	0	0	3	3
TP	Increase	6	0	1	2	0	0	1	2	2	0	1	1	0	0	1	2
PERCENTAGE																	
BU	Decrease	33%	n/a	100%	33%	n/a	n/a	100%	100%	100%	n/a	100%	100%	n/a	n/a	100%	100%
BU	Inconclusive	0%	n/a	0%	67%	n/a	n/a	0%	0%	0%	n/a	0%	0%	n/a	n/a	0%	0%
BU	Increase	67%	n/a	0%	0%	n/a	n/a	0%	0%	0%	n/a	0%	0%	n/a	n/a	0%	0%
CC	Decrease	45%	45%	17%	17%	18%	33%	17%	17%	44%	44%	20%	20%	27%	36%	17%	17%
CC	Inconclusive	18%	18%	17%	17%	36%	33%	8%	0%	22%	22%	10%	10%	27%	27%	8%	8%
CC	Increase	36%	36%	67%	67%	45%	33%	75%	83%	33%	33%	70%	70%	45%	36%	75%	75%
CR	Decrease	6%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
CR	Inconclusive	0%	0%	11%	11%	0%	0%	13%	0%	0%	0%	13%	13%	0%	0%	13%	0%
CR	Increase	17%	0%	6%	6%	0%	0%	6%	0%	21%	0%	0%	0%	0%	0%	6%	0%
DF	Decrease	n/a	n/a	50%	50%	n/a	n/a	n/a	n/a	n/a	n/a	100%	n/a	n/a	n/a	n/a	n/a
DF	Inconclusive	n/a	n/a	0%	0%	n/a	n/a	n/a	n/a	n/a	n/a	0%	n/a	n/a	n/a	n/a	n/a
DF	Increase	n/a	n/a	50%	50%	n/a	n/a	n/a	n/a	n/a	n/a	0%	n/a	n/a	n/a	n/a	n/a
SR	Decrease	40%	40%	13%	27%	40%	40%	27%	27%	40%	40%	13%	27%	40%	40%	20%	27%
SR	Inconclusive	40%	40%	53%	40%	40%	40%	7%	20%	40%	40%	47%	40%	40%	40%	27%	27%
SR	Increase	20%	20%	33%	33%	20%	20%	67%	53%	20%	20%	40%	33%	20%	20%	53%	47%
SWT	Decrease	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SWT	Inconclusive	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
SWT	Increase	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
TP	Decrease	22%	n/a	57%	22%	n/a	n/a	43%	38%	25%	n/a	75%	50%	n/a	n/a	43%	38%
TP	Inconclusive	11%	n/a	29%	56%	n/a	n/a	43%	38%	25%	n/a	0%	25%	n/a	n/a	43%	38%
TP	Increase	67%	n/a	14%	22%	n/a	n/a	14%	25%	50%	n/a	25%	25%	n/a	n/a	14%	25%

Table 6.6: Breakdown of outcomes by apartment complex.

In the remainder of this chapter we focus on the outputs we consider to be the most reliable. As mentioned in Appendix 1, the after sets (for both winter and summer) exhibit seasonal bias and often suffer from a lack of data. We therefore consider the tests using the summer before and winter before α values to be the most reliable, and we rely on these going forward. We show results for the after tests in Appendix C.

Looking at the broadest view of results, all fifty-one participants together, the split between usage decrease, inconclusive, and usage increase is roughly in thirds. In Figures 6.1-6.8 for each test we show the t-statistic distributions for all four interventions, in both seasons, in the after segregation (we display the results for the before analyses in Appendix C). Examining these figures is insightful because if the program had absolutely no effect on any count, one would expect the distributions to be centered on zero and roughly symmetric. The more effective the program is (ie: the more people reduced from before to after), the more shifted to the left these figures should be. Of the eight tests, only two have mean values that are negative and neither of them are significant (greater than a critical t-value at any usual confidence level). We therefore find little evidence of any of the program's events or the program in its entirety having any effect in either direction in this broad stroke analysis.

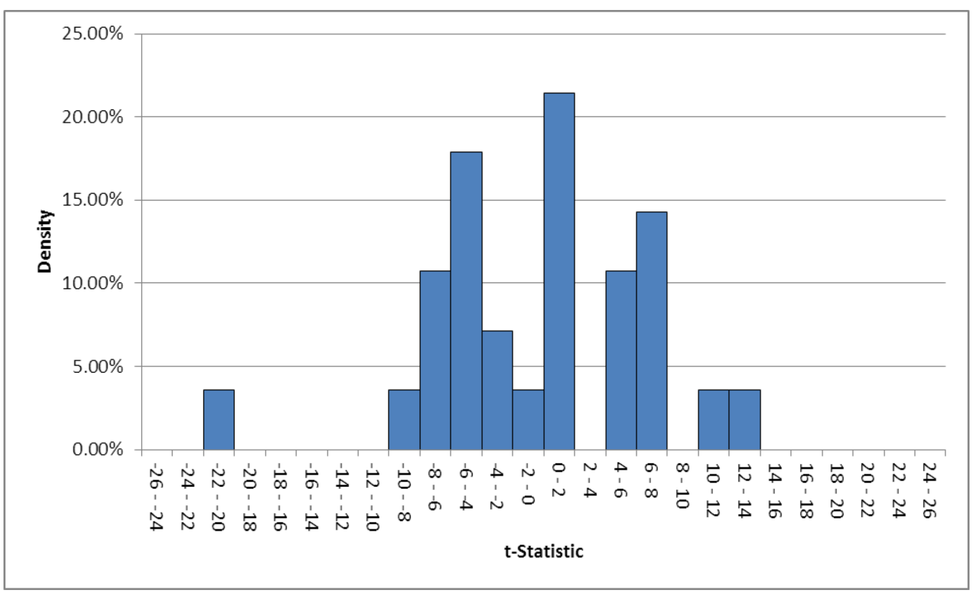

Figure 6.1: T-statistic distribution, E&W, winter, before.

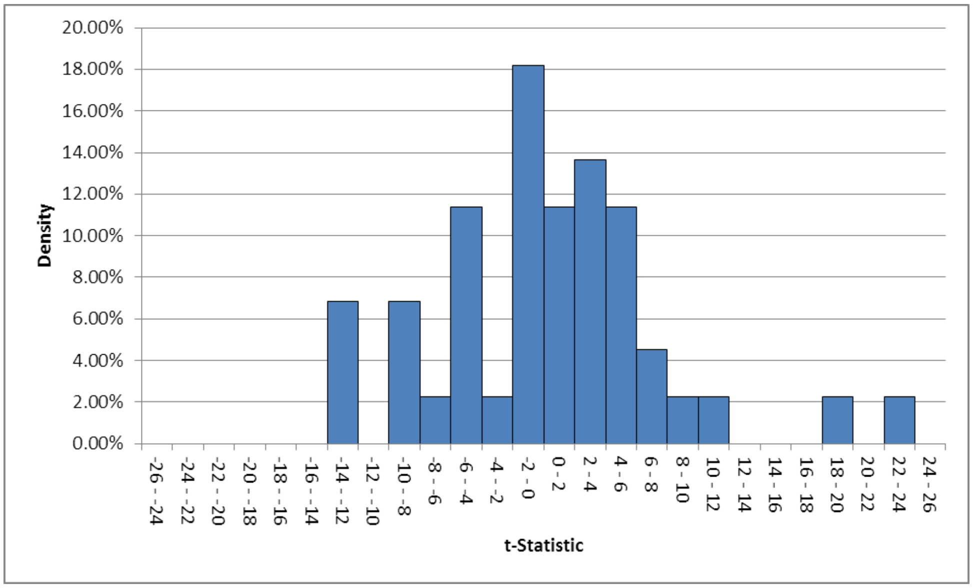

Figure 6.2: T-statistic distribution, E&W, summer, before.

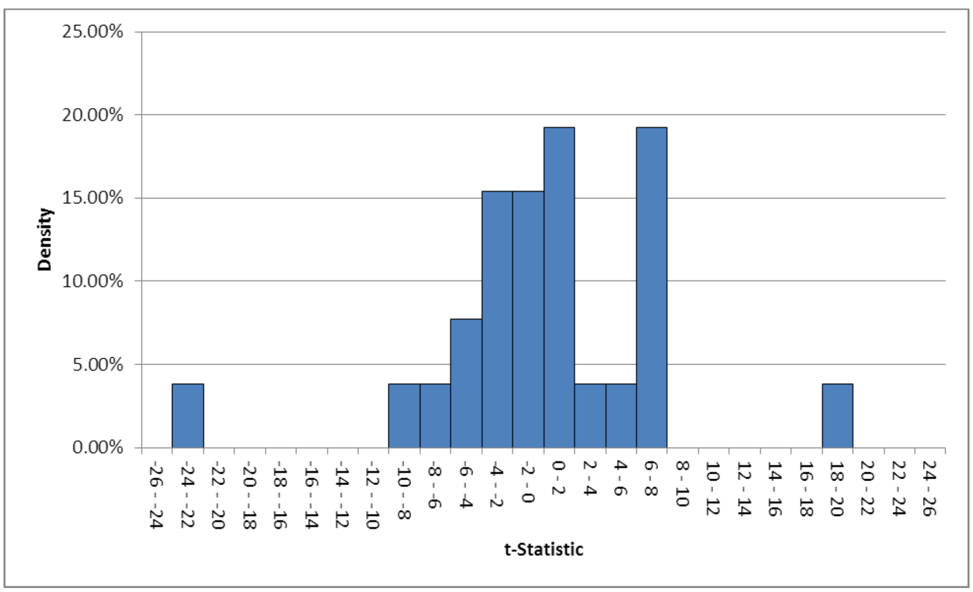

Figure 6.3: T-statistic distribution, energy report, winter, before.

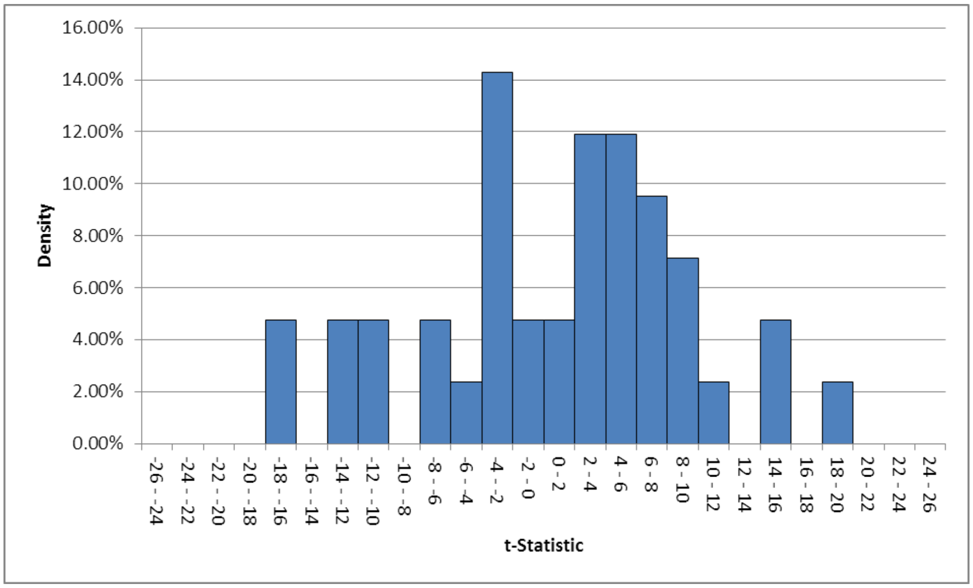

Figure 6.4: T-statistic distribution, energy report, summer, before.

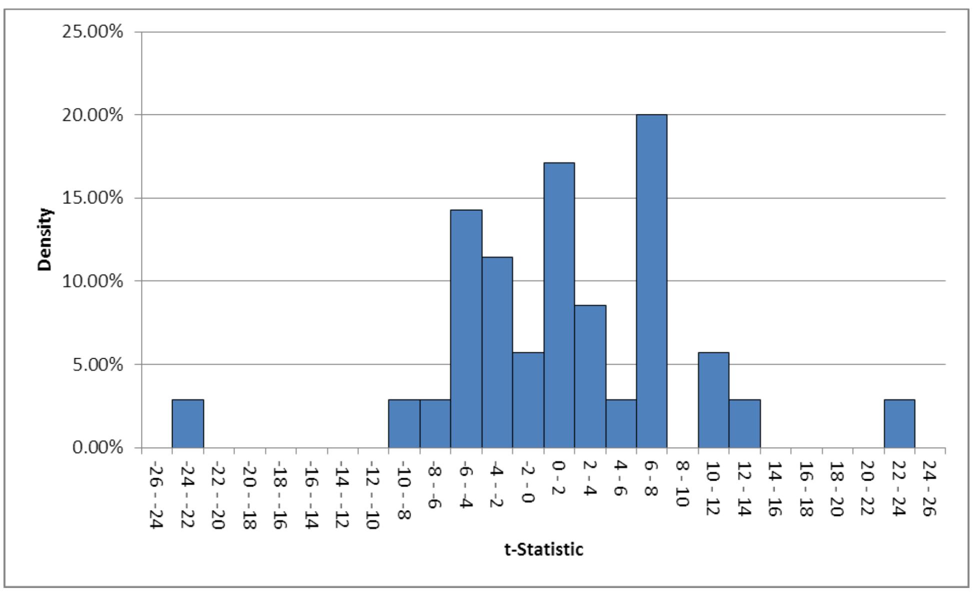

Figure 6.5: T-statistic distribution, energy visit, winter, before.

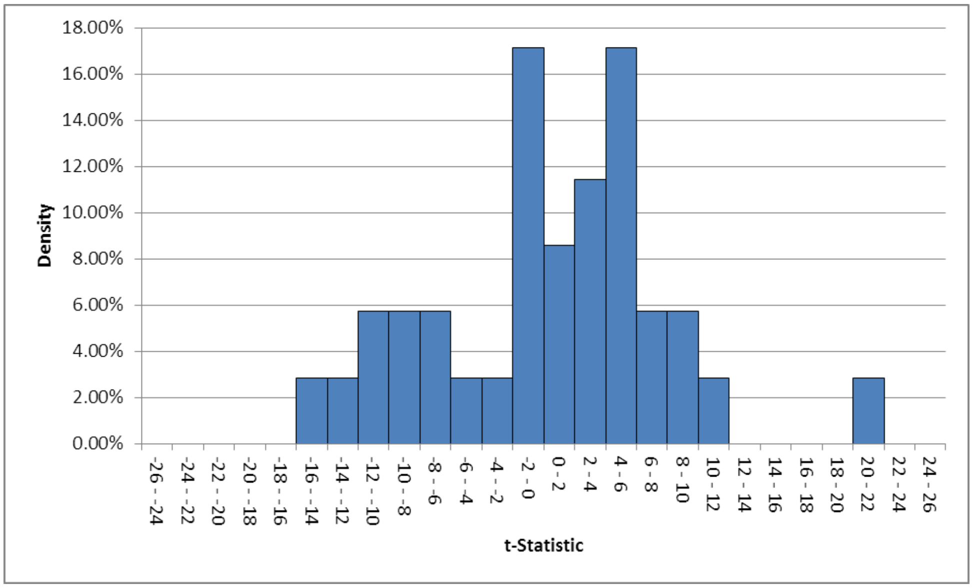

Figure 6.6: T-statistic distribution, energy visit, summer, before.

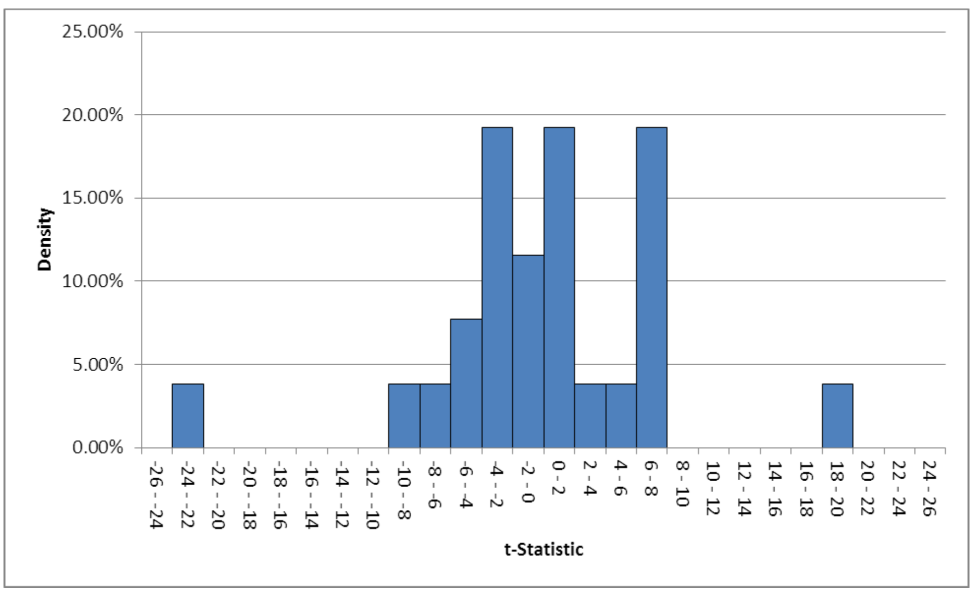

Figure 6.7: T-statistic distribution, entire program, winter, before.

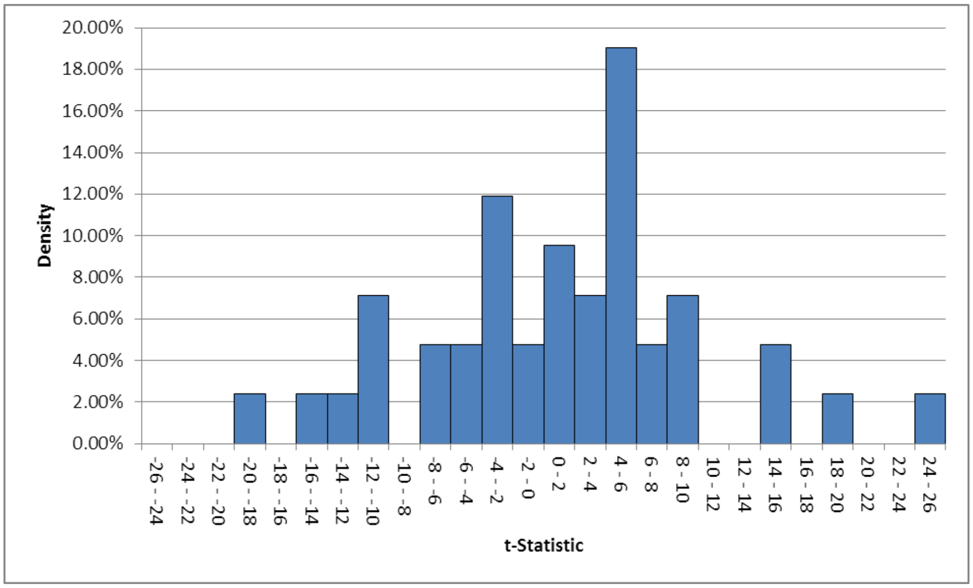

Figure 6.8: T-statistic distribution, entire program, summer, before.

We now focus on the outcomes for program participants. Again, we note that there is a roughly even split between electricity consumption reduction, inconclusive, and electricity consumption increase in most of the analyses. In the winter and summer before analyses it appears that participants whose usage increased usually outnumber those whose usage decreased in most scenarios. However, we do note that the winter results appear to be slightly more favorable.

Comparing Spanish-speaking participant households with English-speaking participant households yields intriguing results. English speakers outperformed the Spanish speakers in every single test using summer months, both in terms of having a higher percentage of participant households whose usage decreased and a lower percentage of participant households whose usage increased. However these results become much more ambiguous in the winter. It is easy to imagine that English speakers might outperform Spanish speakers, as the program's managers are primarily English speakers, and would likely be able to respond better to questions, or present in a more technically sound fashion in their native language. However the fact that English speakers fared so much worse, relatively, in the winter than in the summer is striking. It may be the case that cultural norms play a role here and Spanish speakers are more flexible with non-cooling load that plays a larger role in the winter (in the interviews we did see anecdotal evidence that Christmas lighting is a major load source in Spanish-speaking households). It may also be the case that there was a failure of communication during the energy-visit in instructing Spanish speakers how to reduce cooling load. We also must recall our result of the energy usage analysis that showed Spanish-speaking households allocate less of their usage to the summer, and may have less room to conserve with cooling load.

Turning now to Table 6.5, we see how participants with electric heaters performed relative to those with gas heaters. The results appear very ambiguous and depend on the intervention. One would expect that the performances should be relatively similar in the summer, as the heating system is turned off during those months. In the winter, one would also expect units with gas heaters to perform more poorly, as they have less control over their electricity use and less ability to reduce. Again, the results appear totally ambiguous which seems to imply that there is nothing about the electric or gas-heated units that makes them more or less fertile grounds for electricity use reduction.

In Table 6.6 we consider participants by complex. This dimension appears to create divergence, with some groups outperforming others however it is difficult to identify any consistent patterns. Most of the complexes have too few participants on their own for us to truly identify consistent decreases or increases in electricity consumption; for example complex BU showed 100% of participants reducing in some tests but it only had three participants. Among the three complexes with more than six participants (CC, SR, and TP) we see divergence but again, it is hard to say if any complex performed definitively better. Nonetheless, there is some power in this result as it appears to dispel the idea that any particular complex had an advantage and that due to correlation between language or heating method and complex our results on language are weak. Therefore, we can put more stock in our previous findings.

Combining the results of this chapter with our previous findings in Chapter 5, we cannot definitively say that SGP participants significantly reduced energy consumption. Differentiating the analysis by seasons shows that there may be some gains in the winter; this is more evident in the participant/non-participant comparison in Chapter 5 than it is in the own past-usage analysis in Chapter 6. Summer results are even more modest with both analyses showing minimal impact. All in all, SGP participants seem to have had difficulty in adjusting cooling load while making some gains in the fixed load arena.

Chapter 7: Conclusion

Our analysis makes several efforts to better understand energy usage in low-income households and the impact of energy education. We first conducted a literature review to better scope our efforts. Next, we articulated SGP as an effort to educate low-income energy users in methods of efficient consumption and utility bill reduction. We then conducted a demographic analysis and electricity usage analysis to better characterize SGP participants. Our next step was to interview program participants to understand their perspectives on the program and identify factors that may not have come through in the data. Finally, we undertake two quantitative analyses, one of which takes a difference-in-difference approach to compare groups of participants against groups of non-participants, and another which uses an econometric analysis to compare participants against their own past-usage.

Our literature review revealed that analyzing single residence electricity consumption patterns is much more than an engineering problem. Behavioral factors that may or not be the product of rational choice are of paramount importance. We also learned that low-income residences will likely differ in their energy consumption habits, either due to economic circumstances or more complex mechanisms like social or cultural norms. Our demographic analysis showed us that participant households contained either a single senior occupant, or households with multiple children. Furthermore, we found that the Spanish-speaking participant households contained more children and earned less income on average.

Analyzing electricity usage revealed several results. First, we find that participant households vary in electricity consumption patterns and about 42% of electric load goes to cooling in a gas-heated household. Furthermore, we find that cooling is roughly two thirds of monthly load in the peak months of July and August. Surprisingly, we also found no correlation between income and electricity consumption; unit construction and design seem to dictate most usage patterns. This implies that energy burden is larger for households with smaller incomes.

Interviewing participants revealed that the biggest lesson learned was plug load awareness. Fewer participants retained information about the importance of cooling load, and most are not aware that it is likely the largest user of electricity in their household. It is likely that plug loads were the lower hanging fruit because SGP participants see that load as a total loss, whereas cooling load carries more inherent value and its reduction requires a tradeoff with comfort. Participants' greatest obstacle to reduction seemed to be cohabitants, especially children. We also noted that thermostat set temperatures were usually very high to begin with. These two facts combined create a picture of a community that has little flexibility in reducing to begin with. Finally, we also learned that participants readily disseminated information within their household, and to the broader community.

Our two quantitative analyses showed some evidence of program impact in winter, and almost no evidence of program impact in the summer. We note that this is largely consistent with the results of our interview analysis, where participants generally focused on their efforts to reduce plug loads, and had little awareness of the importance of the thermostat. We note that English participant speaking households fared relatively better in the summer than in the winter and the reasons for this remain unclear, however it may have something to do with Spanish-speaking participant households using less cooling load to begin with, and communication issues during the program's presentation.

Acknowledging these results and synthesizing them into a broader understanding can yield recommendations for the future. The reality is that consumption is low and fairly inflexible for most households for a variety of reasons. There are just a few outliers (see Figure 3.4) with abnormally high electricity consumption and the reasons for their high electricity usage are likely very individual-specific. This group might afford the greatest opportunity for energy conservation. Therefore, a blanket approach in the form of a program for all participants may not be optimal. Rather, targeted investigations of individual households that likely have massive cooling inefficiencies could be a better path forward. Furthermore, the problem of information retention must be grappled with. Further targeted efforts should focus on ensuring continuity of habits rather than purely information delivery. It is not enough to inform a person; rather they must be continuously reminded until there is a fundamental shift in their behavior that allows them to reconcile context and incentives.

Appendix A: Calculation of Load Sensitivity to Temperature

We show the sixteen α values for each participant in Table 6.1. In an attempt to validate our assumption that the analysis should be seasonally segregated, we conduct a t-statistic test on the difference between winter and summer α values for each participant for each intervention (this will yield eight t-statistics in total). Using equation (10), we can calculate a t-statistic based on the average difference between winter and summer α, the standard deviation of these differences, and the number of participants. We take care to remove participants who had insufficient data to calculate an α value. We show the results in Table A.1.

	E&W		ER		EV		ALL	
	Before	After	Before	After	Before	After	Before	After
Avg. of α_{Winter}-α_{Summer}	-0.74	-0.76	-0.74	-0.67	-0.78	-0.75	-0.74	-0.67
Standard Deviation	0.41	0.31	0.38	0.28	0.37	0.31	0.41	0.28
N	43	30	43	27	34	27	43	27
t-Stat	-11.80	-13.46	-12.87	-12.51	-12.22	-12.57	-11.80	-12.51

Table A.1: Statistical analysis of difference between winter and summer α values .

All t-statistics are highly negative and significant at any conceivable confidence level. This implies that household sensitivity to energy use is highly season specific and we consider this ample justification for our seasonally segregated analysis.

As a test of our belief that α should not change from before to after the workshop, we repeat the above analysis but calculate the difference between before and after α values for each season and each test (again, a total of eight t statistics will result). We show the results in Table A.2.

	E&W		ER		EV		ALL	
	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer
Avg. of α_{Before}-α_{After}	-0.07	-0.01	-0.10	0.01	-0.07	0.00	-0.10	0.00
Stdev	0.12	0.32	0.14	0.87	0.11	0.33	0.14	0.87
n	28	44	26	39	26	34	26	39
t-Stat	-3.13	-0.11	-3.62	0.07	-2.90	-0.08	-3.52	0.03

Table A.1: Statistical analysis of difference between before and after α values.

The results show no significant variation in any of the summer tests however we do see statistically significant variation in the winter tests. Again, we hypothesized that there should be no statistically significant difference, so this is somewhat perplexing. Furthermore, all winter tests consistently show that α values calculated with data from after SGP Program are higher than those calculates using data from before.

A possible answer for the variance in winter α values from before to after the workshop may lie in the general lack of data we have for winter months occurring after the workshop. In many cases we only have the months of March and April. Although we classify these months as winter, it is relatively common for air conditioning units to be at least somewhat active during these months. This means that participants who have only March and April data are likely to show a much more positive α value than they would if they had the entire winter. When the entire winter is included, α should be relatively close to zero due to the absence of cooling (although if electrical heating systems are operating, then αwill likely be negative). Therefore participants will show a sharp jump in winter α when they have this data problem. We attempt to test this hypothesis by removing all participants who have less than four months of data available for either the winter before the Energy and Water Workshop, or the winter after the Energy and Water Workshop. This reduces the t-statistics to -2.59, -3.22, -2.29, and -3.15. There is a change, but there still appears to be statistical significance. Therefore the seasonal bias issue cannot account for all of our variance in the winter α values.

One more hypothesis that would explain the variation in the winter α values is that our assumption of linearity may be faulty. It is possible that energy usage may be more sensitive to changes in temperature at hotter or colder temperatures. We note that the first winter of our analysis, 2008-2009, saw an average temperature of 59.53 degrees, the second winter, 2009-2010, saw an average of 54.89 degrees, and the third winter, 2010-2011, saw an average of 59.70 degrees. All of our winter after data comes from the last value, which was the hottest winter. One would expect that winter α values would be more positive then because more cooling is operating. Out t-statistics are negative, implying that winter αvalues are in fact higher on average. It is therefore possible that, seasonal bias aside, the warmer winter occurring after the workshop caused a nonlinearity to occur in the relationship between energy usage and temperature.

In summary, our analysis shows that seasonal segregation of α values is justified. We observe that α values for summer months show no significant difference from before to after the workshop. However α values for the winter months appear to show a jump. Although we initially suspected seasonal bias, it is likely that the difference in climate between winters before and after the workshop hampered the analysis. The greater operation of cooling systems in the winter of 2010-2011 may have caused a non-linearity that causes α values from the winter after the program to be more positive. The implication for our result is that our assumption of constant α values from before to after the workshop may in fact be faulty, and therefore the t-statistics for the winter tests must be taken more cautiously.

Appendix B: Testing for Linearity

In order to validate our approach, we conduct a test to see if a linear model is appropriate when defining energy usage as a function of monthly average temperature. Nonlinear relationships are certainly possible. One can hypothesize that as temperatures rise to very high levels in the summer, air conditioning units may be operating at 100% capacity all day long and any incremental increase in temperature does not result in more electricity consumption. The opposite scenario, where electric-resistance cooling is constantly in operation, is not relevant to the Central Texas climate.

Our linearity test looks at whether our model consistently over or underestimates energy usage in a given month with a given temperature. We begin by simplifying equation (1) to the following

$$E_{a,i} = G_{a,i} + \alpha_{a,i} T_a \qquad (10)$$

Note that this implies that $G_{a,i} = F_{a,i} - \left(\alpha_{a,i} C_{a,i}\right)$. We find a G and α values for each participant, in each season (summer and winter). The analysis is therefore segregated by season. We use this model and the given temperature in each month to calculate an estimate of what energy usage in a given month should be, in kwh/day. We then subtract the observed kwh/day value from our estimate to arrive at a residual. There is one residual for each month, for each participant. We take advantage of the fact that all participants are in Austin, Texas, and observed the same temperatures (billing periods were all comparable to the point of temperature differences being negligible). This allows us to simultaneously cluster our residual values by month and temperature.

Next, we conduct a t-test on each month (or temperature value) to see if the residuals are statistically different from zero. If the t-statistic is too high for a given month or temperature, we are consistently overestimating energy usage in that month or at that temperature. If it is too low, we are consistently underestimating energy use in that month or at that temperature. If a linear model is a good fit, residuals should not differ significantly from zero. If we observe the tapering off effect at high temperatures where air-conditioners are constantly on and increases in temperature do not cause further increases in energy usage, we would expect that the model would consistently overestimate energy usage at the highest temperatures. If there is another effect at work that causes energy usage to accelerate as temperature increases, we would expect to find consistent underestimates at high temperatures.

We show a clustered scatter plot of the residuals in Figure B.1-B.2, and the results of our t-statistic tests in Table B.1-B.2.

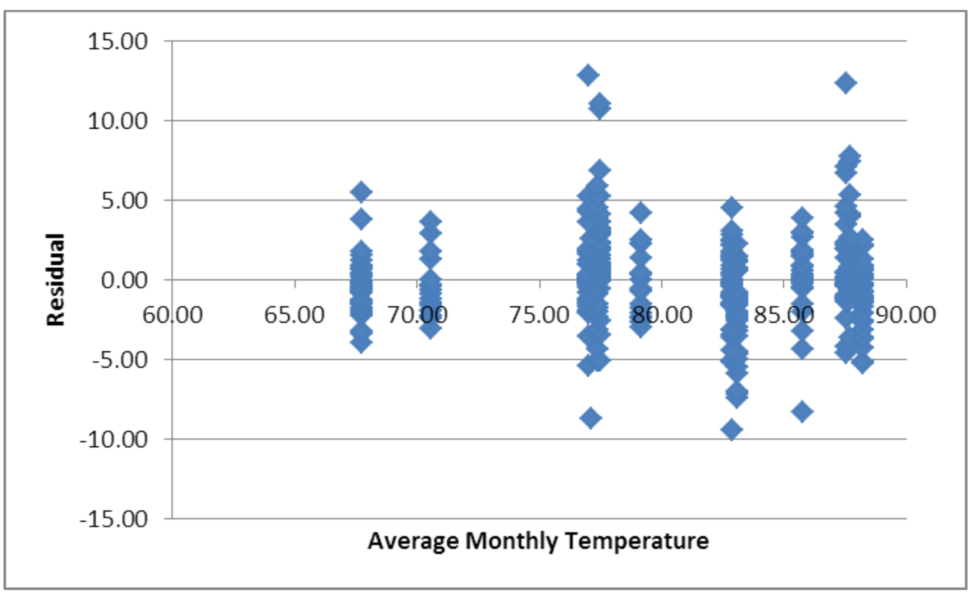

Figure B.1: Scatter plot of summer electricity usage model residuals.

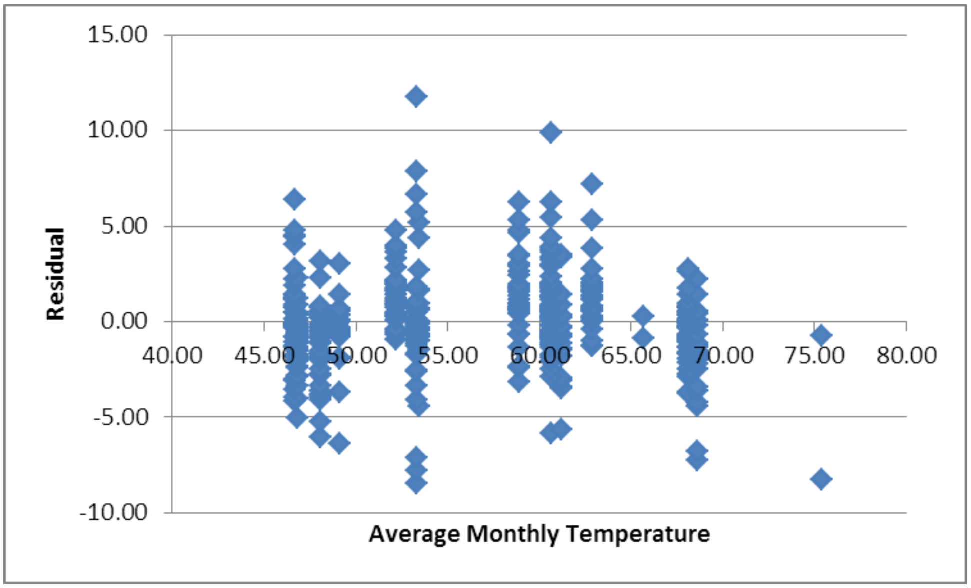

Figure B.2: Scatter plot of winter electricity usage model residuals.

Average Monthly Temperature	Avgerage Residual	Standard Deviation	Count of Participants	t-Statatistic
88.22	-1.00	1.88	37	-3.25
87.68	1.02	2.42	38	2.59
87.56	1.03	3.46	29	1.61
85.77	0.14	2.27	33	0.35
83.08	-2.03	2.42	40	-5.30
82.87	-0.51	2.59	44	-1.32
79.15	-0.19	2.09	18	-0.39

Table B.1: Scatter plot of electricity usage residuals in summer.

Average Monthly Temperature	Avgerage Residual	Standard Deviation	Count of Participants	t-Statatistic
75.38	-4.51	5.32	2	-1.20
68.60	-1.79	1.97	32	-5.13
68.14	-0.52	1.48	41	-2.26
65.70	-0.32	0.79	2	-0.57
62.87	1.36	1.78	30	4.21
61.23	-0.89	2.31	19	-1.69
60.68	0.19	2.37	39	0.51
60.65	1.60	1.91	30	4.59
58.89	1.37	1.99	40	4.34
53.44	0.44	2.12	19	0.90
53.33	-0.23	2.82	20	-0.37
53.33	-0.10	4.43	20	-0.10
52.18	1.47	1.47	29	5.38
49.12	-0.57	1.86	21	-1.41
48.09	-1.24	1.91	40	-4.10
46.83	-1.13	1.39	39	-5.04
46.69	0.39	2.35	40	1.05

Table B.2: Scatter plot of electricity usage residuals in winter.

All in all there appears to be no specific pattern. We either over or underestimate energy usage roughly half the time. Furthermore there is no consistent pattern of over or estimation, for example, consistent underestimation at high levels due to the tapering off effect. The key takeaway for us is that averaged monthly temperature data may not be sufficient for a precise modeling effort. The average temperature may say nothing of what the actual demand for cooling is. One can imagine an average March, where temperatures are consistently at the cusp of igniting cooling demand, without actually requiring it. A monthly with slightly cooler temperatures for twenty four out of thirty one days but with a one week-long heat wave will result in a major spike in cooling demand. The two months would have the same average temperature, but significantly different energy demands. The implication of this is that future studies may wish to consider higher resolution data, either daily or hourly.

Appendix C: Results for Alternative Tests

In this section we display the t-statistic distributions for all statistical tests using α values generated with data occurring after each participant attended the SGP energy and water workshop. The results are largely consistent with those displayed in Chapter 6.

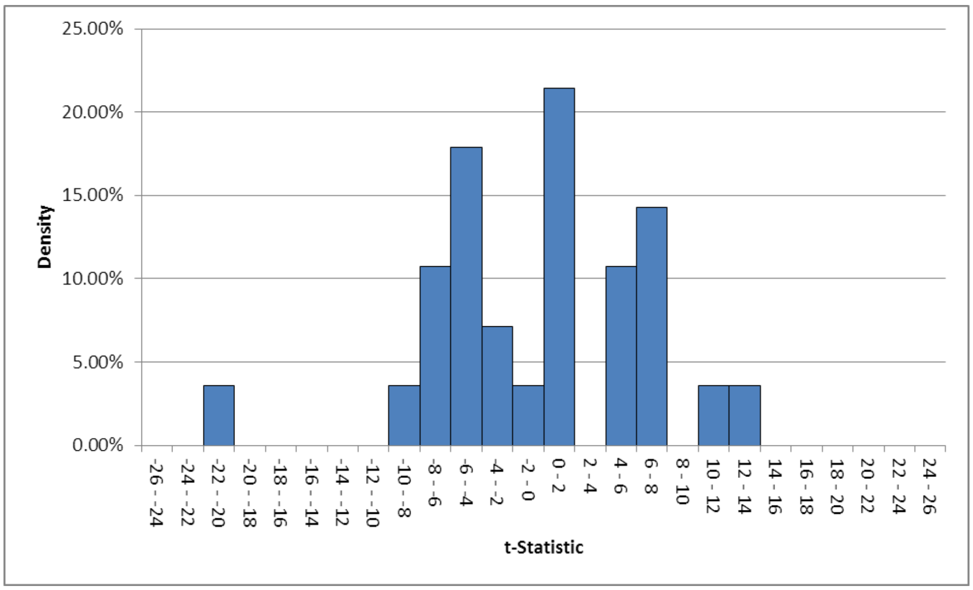

Figure C.1: T-statistic distribution, E&W, winter, after.

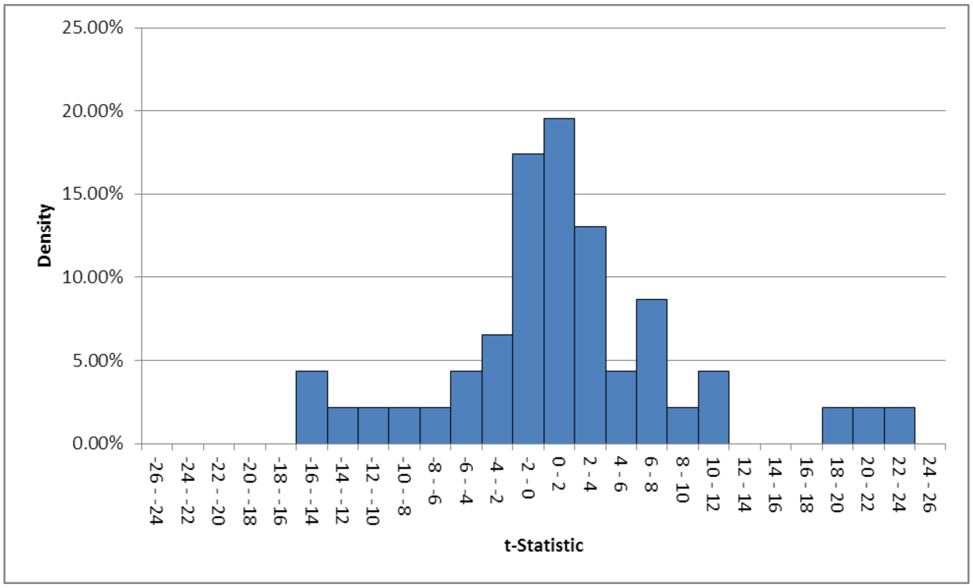

Figure C.2: T-statistic distribution, E&W, summer, after.

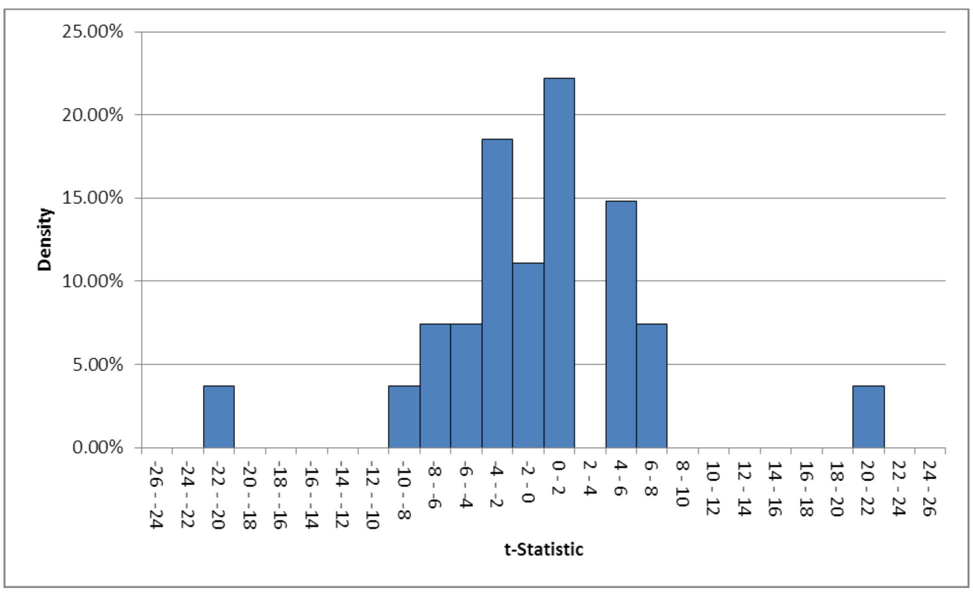

Figure C.3: T-statistic distribution, energy report, winter, after.

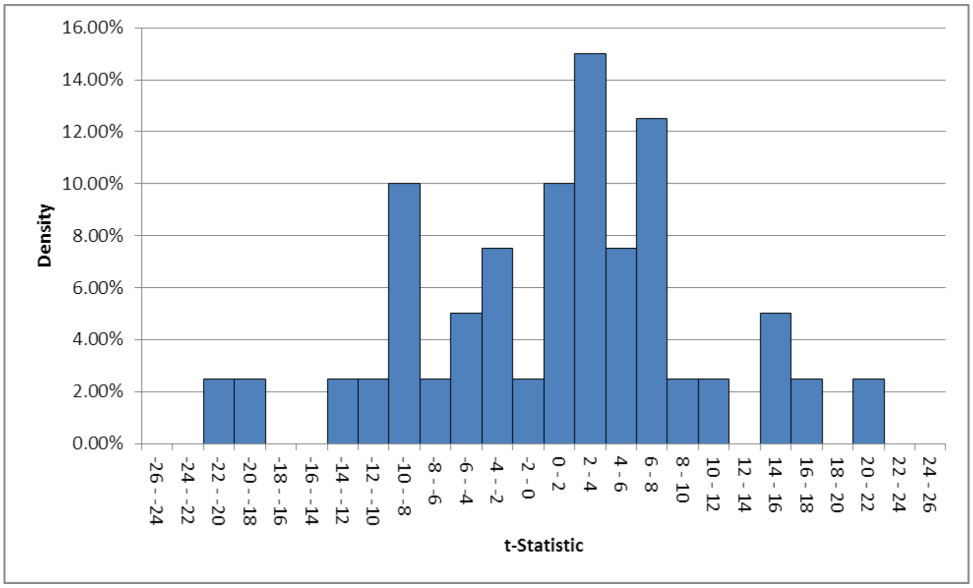

Figure C.4: T-statistic distribution, energy report, summer, after.

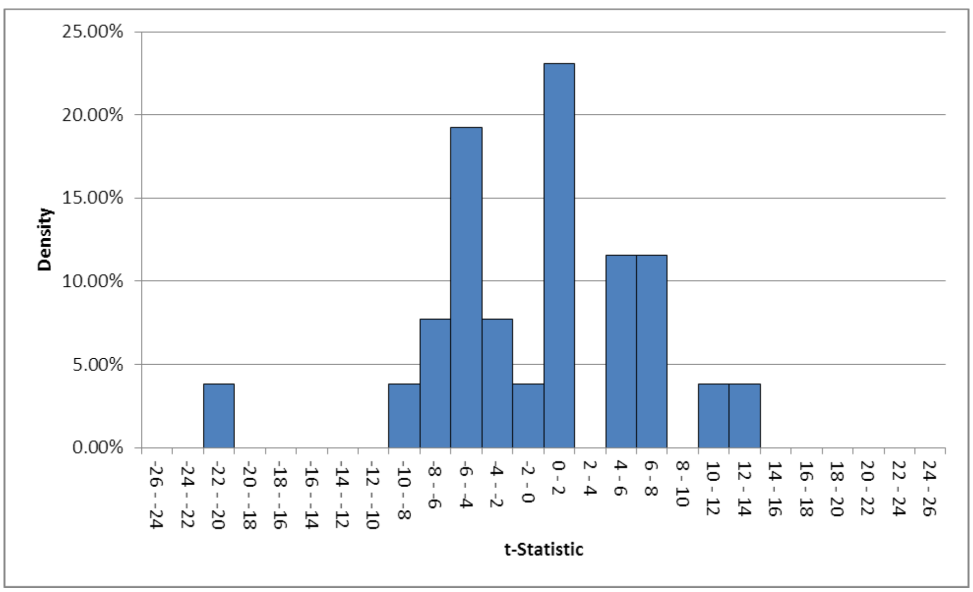

Figure C.5: T-statistic distribution, energy visit, winter, after.

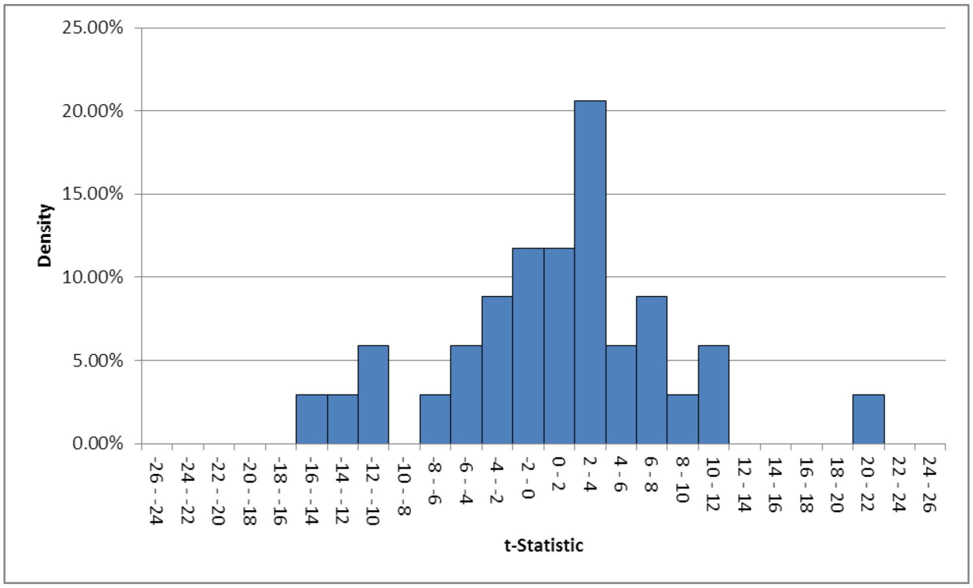

Figure C.6: T-statistic distribution, energy visit, summer, after.

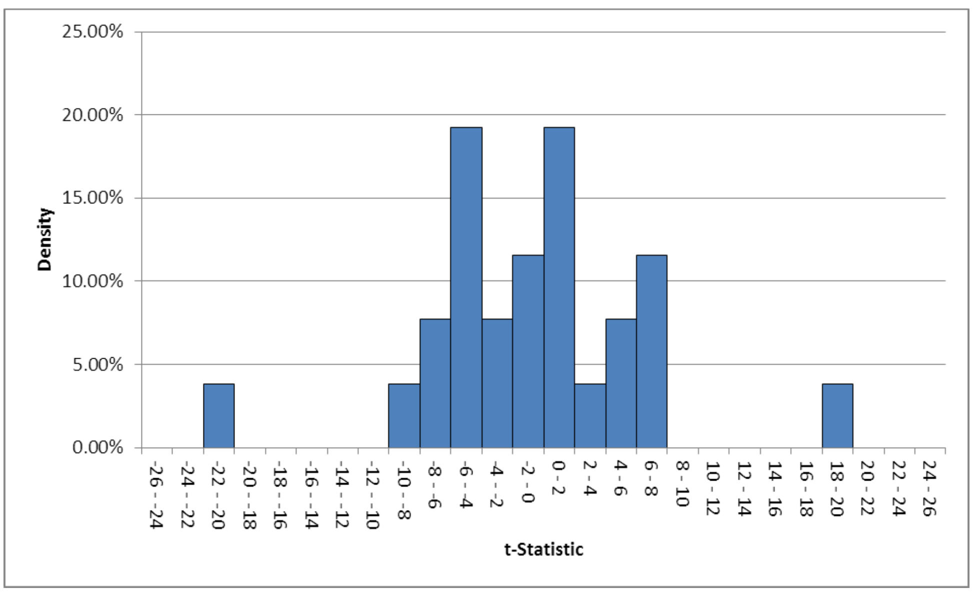

Figure C.7: T-statistic distribution, entire program, winter, after.

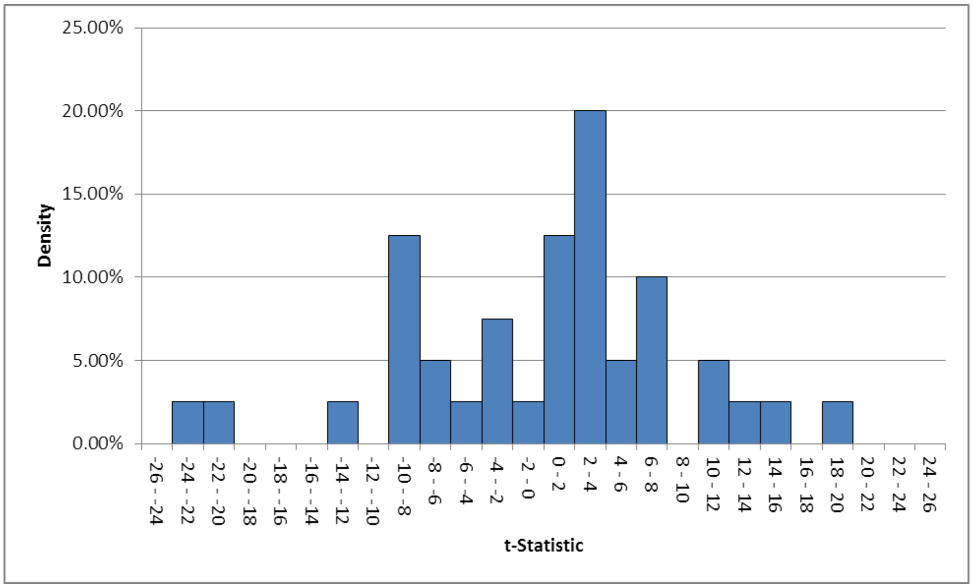

Figure C.8: T-statistic distribution, entire program, summer, after.

Glossary

VARIABLES

Symbol	Indexes	Definition	Description
α	a,b,i,p	$\alpha = {}^{\Delta E}/_{\Delta T}$	Sensitivity of household energy use to change in temperature. Residence specific parameter, not under participant control.
C	a,b,i,p	$C = \frac{E - F}{\alpha} - T$	Internal thermal preference. Residence specific, and expected to change from before to after intervention. Under control of residence occupant.
D	i,a*b	$D = \Delta E - \alpha(T_a - T_b) = \alpha(C_b - C_a)$	A single occurrence of the difference in temperature corrected energy use from one month before the intervention to one month after the intervention.
$\overline{D}$	i,p	$\overline{D} = \sum_{a,b} D_{a,b}$	The average of differences in temperature corrected energy use from months before the workshop to months after the workshop. A proxy for observed program impact.
E	i,t	$E = F + \alpha(T - C)$	Electricity usage by a residence in a given month in kwh/day.
F	i,t	$F = E - \alpha(T - C)$	Energy usage that is not affected by temperature, for example lighting, appliances, and plug loads.
T	t, a, b	n/a	Average monthly temperature in Austin (F)

INDEXES

Index	Definition	Description
a	n/a	Months occurring after the defined intervention.
b	n/a	Months occurring before the defined intervention.
i	n/a	Participant
p	(summer before, summer after, winter before, winter after)	The seasonal and before/after segregation of our tests
t	Union(a,b)	Month, time

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